

Home Is Where Your FinTech Loan Is*

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Abstract

I study the spillover effect of unsecured FinTech lending on mortgage markets. Using quasi-exogenous variation in LendingClub loan activity due to its partnership with the BancAlliance consortium of community banks in February 2015, I present causal evidence that increase in unsecured personal loans by LendingClub resulted in a significant increase in overall mortgage activity in an area. This spillover is more pronounced for new home purchase activity versus mortgage refinancings, and for borrowers who face larger information frictions in the mortgage market. Despite the increase in mortgage lending, I show that mortgage default rates did not increase. Overall, my findings uncover a new benefit of FinTech lending and provide important inputs to ongoing policy debates in the unsecured FinTech lending market.

Keywords: FinTech lending, Mortgage lending, Information frictions

JEL Classification: G20, G21, G23

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One of the primary objectives of financial intermediaries is to reduce information frictions in credit markets. Traditionally, they have achieved this by using a variety of screening devices such as requiring borrowers to post collateral, or by offering them a menu of contracts. While these devices allow lenders to distinguish between borrowers who are creditworthy and those who are not, some still face financing frictions and are denied credit ([Gorton and Winton, 2003](#)). Mechanisms and institutional arrangements that alleviate these frictions have a first order impact on the efficiency of credit markets, as well as on the welfare of borrowers. Can recent advances in lending technologies, such as the significant rise of FinTech lenders, improve subsequent outcomes in credit markets for these borrowers?

To address this larger question, I examine the impact of unsecured FinTech lending on borrowers' access to the U.S. mortgage market. While several studies have explored the impact of FinTech lending within its own market, my paper is among the first to examine its spillover effects on the mortgage market in a causal manner. On one hand, FinTech lenders can alleviate credit market frictions by using superior screening technology and alternative data, thereby improving credit access for new and existing borrowers through cheaper debt consolidation and the provision of new loans ([Berg, Burg, Gombović, and Puri, 2020](#); [Di Maggio, Ratnadiwakara, and Carmichael, 2022](#)). On the other hand, if FinTech lenders are merely “skimming” the best borrowers from the existing pool, or if borrowers use FinTech loans for conspicuous consumption, their presence might not lead to any substantial improvement in borrower outcomes ([Di Maggio and Yao, 2021](#)). Therefore, my study sheds light on an important and unresolved empirical question.

In addition, my study is important for two other reasons. First, unsecured FinTech lending has grown tenfold over the past decade, while the mortgage market represents a substantial share of household debt in the U.S., making this an economically significant setting.^{1,2} Second,

¹Source: Transunion

²[Iacoviello \(2011\)](#) find that two-thirds of the wealth of a median U.S. household consists of housing wealth. For the bottom 90% wealth group, [Smith, Zidar, and Zwick \(2021\)](#) show that 62% of non-pension wealth is composed of housing.

as FinTech loans are typically smaller than mortgages, my study provides insight into whether small, cash-flow-based lending can help facilitate access to larger, collateral-based loans. This can be particularly relevant when collateral alone is insufficient to address information frictions between lenders and borrowers (Besanko and Thakor, 1987; Benmelech, 2024). Thus, improvements in traditional credit metrics, such as repayment history, debt-to-income ratio, and credit scores resulting from cash-flow-based lending, could further enhance borrowers' access to collateral-based loans.

I empirically examine the effect of unsecured FinTech loan originations, measured using LendingClub data, on the outcomes in the mortgage market, measured using HMDA data, during 2010 to 2019. I combine these two datasets and aggregate them at 3-digit zip code level, or zip3 level, to analyze how the growth of unsecured FinTech lending influences mortgage market outcomes across over 900 zip3 areas in the US. Since borrowers often receive preliminary indications from lenders about their likelihood of obtaining a mortgage before they formally apply, I use both the number of mortgage applications and the number of loans originated as measures of mortgage activity in each area. To control for any time-invariant local characteristics, I employ zip3 area fixed effects. Additionally, I include the interaction of state and year fixed effects to account for any time-varying changes in state-level factors, such as economic growth, fiscal policy, regulation, and demographics. Furthermore, by regressing mortgage activity on lagged values of LendingClub loan activity, I address potential concerns about reverse causality between the two markets. I find a positive correlation between LendingClub loan activity and overall mortgage activity in an area in this baseline specification.

Is this relationship causal? Unobserved time-varying factors, such as economic growth and job opportunity, may simultaneously drive both FinTech lending and mortgage activity within an area. To address this endogeneity concern, I employ a novel identification strategy based on the February 2015 partnership between LendingClub and the BancAlliance network, one of the largest consortium of community banks in the US. A key aspect of this partnership

was that BancAlliance member banks would redirect their unsecured personal loan customers to the LendingClub platform, enabling LendingClub to significantly expand its borrower base in areas where these banks operated. Since the partnership with the BancAlliance network was established at the national-level, LendingClub could not selectively target specific areas to expand its borrower base. This makes the increase in LendingClub loan activity exogenous to mortgage outcomes and growth at the zip3 level. Furthermore, this arrangement also prevented LendingClub from selling mortgage or other products to bank customers.³ BancAlliance member banks, who were primarily small community banks, entered the partnership to invest in securitized LendingClub loans in order to diversify their credit portfolios with unsecured consumer loans rather than expand mortgage lending. This quasi-exogenous expansion of LendingClub loan activity provides a unique opportunity to causally identify the impact of unsecured FinTech lending on mortgage market outcomes in an area.

At the time, BancAlliance had over 200 member banks across 39 states, with member banks being small community banks with assets between \$200 million and \$10 billion. To appreciate the scale of this network, it is helpful to note that if all its member banks formed a single entity, the BancAlliance network would rank fourth in the country by branch count and seventeenth by asset size.⁴ Areas where BancAlliance member banks operated during the 2015 partnership with LendingClub are designated as treated areas, while all other areas in the U.S. serve as control areas. I use a standard difference-in-differences specification to compare outcomes in LendingClub and mortgage activity before and after 2015 across treated and control areas. I find that the number of LendingClub loans increased by 9.25% in treated areas compared to control areas after the 2015 BancAlliance partnership, highlighting the significant effect of this partnership on LendingClub loan activity. In my main test using the same difference-in-differences specification, I show that mortgage activity in treated areas increased by nearly 3% relative to control areas after 2015. Moreover, I show that before

³*LendingClub And Smaller Banks In Unlikely Partnership*, Wall Street Journal, June 2015

⁴*LendingClub's Newest Deal Fuels Investor Excitement*, Wall Street Journal, February 2015

2015, treated and control areas exhibited parallel trends in both mortgage applications and loan originations.

To directly link LendingClub loans to mortgages, I use a two-stage regression specification using instrumented difference-in-differences (DDIV) approach (Duflo, 2001; Hudson, Hull, and Liebersohn, 2017). The first stage is a standard difference-in-differences specification, as described earlier, where I estimate the impact of the BancAlliance partnership on LendingClub loan activity in an area. In the second stage, I assess the sensitivity of mortgage activity to unsecured FinTech loan activity, instrumented by the 2015 BancAlliance partnership from the first stage. I observe two key findings. First, there is a statistically significant positive spillover effect from LendingClub loan activity to mortgage activity within an area. On average, a 1% increase in LendingClub loans led to a 30-40 basis point increase in mortgage applications and loans. Second, this effect is smallest immediately after the increase in LendingClub loans and grows larger over time. This pattern is consistent with the gradual improvement in borrowers' traditional credit metrics, driven by FinTech lenders' ability to identify creditworthy borrowers and alleviate information frictions even beyond the unsecured loan market. Additionally, using the same difference-in-differences specification, I find that mortgage interest rates declined by 1.62% in treated areas compared to control areas after 2015. This result, combined with the observed increase in mortgage quantity, suggests an outward shift in the credit supply curve in the mortgage market following the quasi-exogenous increase in LendingClub loan activity, as instrumented through its 2015 partnership with the BancAlliance network.

What is the magnitude of this spillover effect? In the DDIV specification, I find that a one percent increase in LendingClub loans results in approximately a 30-40 basis point increase in mortgage activity in an area. Given that the average number of LendingClub loans is 335, and the average number of mortgage loans is 10,570 in an area in my sample, the DDIV specification suggests that three additional LendingClub loans lead to about 32 extra mortgage loans. This indicates a multiplier effect in the spillover from LendingClub

loan activity to mortgage activity.

There are four possible explanations for this multiplier effect. First, borrowers vetted and approved by the LendingClub platform may use the loan terms they receive as leverage to obtain an unsecured loan from a bank.⁵ Second, banks may interpret a FinTech platform’s decision to offer a loan as a positive signal, prompting them to extend an unsecured loan to these borrowers (Balyuk, 2023). Third, once a LendingClub borrower secures a mortgage, they may decide to refinance it—sometimes more than once—resulting in multiple loans for the same borrower in the mortgage market data. Finally, the IV estimates here represent the effect of the treatment on the subset of areas that are affected by the instrument, i.e. the compliers. This group may respond more strongly to the treatment than the average area captured by the baseline OLS specification, making the IV estimate larger. Consequently, the large value of elasticity here is in line with the interpretation that because the complier areas have a higher sensitivity to treatment (Jiang, 2017).

What is the economic mechanism behind my findings? FinTech lenders can use alternative data and their superior processing technology to identify creditworthy borrowers in the unsecured loan market, and consequently arm them with cheaper debt consolidation loans that help them improve their traditional credit metrics, which is crucial to facilitate the spillover effect from unsecured loan market to secured mortgage market. I check this mechanism using two tests. In these tests, I examine the varying levels of information asymmetry across both borrower types and mortgage products in the mortgage market. First, different mortgage products also present varying degrees of information barriers. For example, new home purchases typically involve greater information asymmetry for borrowers to overcome, whereas refinancings generally carry lower information frictions due to the borrower’s ability to secure a mortgage in the past. Second, some borrowers, such as middle-income individuals, are more likely to face higher information frictions compared to other borrowers.

⁵Obtaining loan terms from LendingClub would not only improve the informativeness of borrowers but also reduce their search costs. This would further aid borrowers to get favourable unsecured loan contracts from traditional lenders (Argyle, Nadauld, and Palmer, 2023).

In the first test, I consider the varying levels of information asymmetry in the mortgage market based on the type of mortgage product. For new home purchases, the information gap between lenders and borrowers should be larger compared to refinancings, where borrowers are already repaying an existing mortgage. Therefore, I compare the sensitivity of new home purchase versus refinancings to LendingClub loan activity in an area. I find that new home purchases are more sensitive to LendingClub loan activity than refinancing activity. Using a triple differences regression specification to compare treated versus control areas before and after the 2015 BancAlliance partnership, I show that, when compared to refinancings, new home purchase applications increased by 3.5% and loan originations increased by 4.6% in treated areas post 2015, versus control areas.

The second test examines the impact of alleviating information asymmetry across different income bands in the mortgage market. I find that, conditional on borrowers applying for a mortgage, middle-income borrowers are the most sensitive to increases in LendingClub loan activity in an area. This result aligns with the information frictions mechanism. This is because if the spillover effect were solely driven by access to cheaper debt consolidation loans, low-income borrowers would be expected to show the greatest sensitivity. However, the higher relative sensitivity among middle-income borrowers suggests that FinTech lenders effectively identify creditworthy individuals, who stand to lose the most if denied access to unsecured FinTech loans.

Are the new mortgages facilitated by LendingClub loan activity riskier than average? To assess this, I study the performance of mortgages originated as a result of increased unsecured LendingClub loans, using Fannie Mae and Freddie Mac data. Employing a DDIV regression design, with the 2015 LendingClub partnership with BancAlliance as the instrument, I provide causal evidence that the rise in mortgage loans due to increased LendingClub activity does not lead to higher mortgage delinquencies. This finding suggests that the spillover from unsecured FinTech lending to the mortgage market is driven by FinTech lenders' ability to use alternative data and superior screening technology to identify previously excluded but

creditworthy borrowers.

To support my main findings, I conduct two robustness tests. First, I replicate my main findings using HMDA mortgage data, excluding all mortgage activity generated by FinTech lenders in the mortgage market. This test shows similar results to my main findings and helps eliminate the possibility that the impact of unsecured FinTech loan activity on mortgage activity is driven by FinTech lenders in the mortgage market. Second, I replicate my main results using Fannie Mae and Freddie Mac mortgage data. The results are similar to my main findings, further substantiating the use of Fannie Mae and Freddie Mac data to study mortgage performance.

My findings carry important implications for borrowers in the mortgage market. Despite numerous policy initiatives and regulatory efforts in the U.S. over the past few decades to increase access to the mortgage market, significant frictions exist in credit markets for marginal borrowers. My study shows that technology enabled market-based mechanisms can be a promising tool to alleviate these frictions. Although my study does not directly assess the welfare effects of FinTech lending, it highlights a significant benefit: FinTech lending can improve mortgage access. This finding is crucial for comprehensive welfare evaluations, as recent concerns from regulators and policy advocates have raised questions about the use of alternative data by unsecured FinTech lenders and its potential impact on fair lending practices (Di Maggio et al., 2022), as well as on privacy. My study provides an essential input to this broader welfare analysis by documenting one of FinTech lending's positive effects on credit market access.

Related Literature

This paper is among the first to provide causal evidence of the spillover effects of unsecured FinTech lending on secured mortgage loans. Three related papers here are studies by [Chava, Ganduri, Paradkar, and Zhang \(2021\)](#), [Balyuk \(2023\)](#), and [Dore and Mach \(2022\)](#), each of

which contributes to the understanding of the broad role of unsecured FinTech lending on borrowers, but with different focuses and findings. First, [Chava et al. \(2021\)](#) compare the credit scores and default rates of borrowers of an anonymous FinTech marketplace lender (MPL) with bank borrowers, as well as with borrowers who were denied unsecured personal credit by both the MPL and banks. They find that MPL borrowers initially experience a rise and eventually experience declines in credit scores. Moreover, they experience higher default rates in the unsecured personal loan market.

Second, [Balyuk \(2023\)](#) uses loan-level data from Prosper to demonstrate that Prosper borrowing increases access to revolving bank credit by alleviating information frictions. While her findings align with my results regarding the short-term improvement of credit profiles due to Prosper borrowing, her focus is on the spillover within the unsecured loan market. In contrast, this paper provides causal evidence of spillover from the unsecured FinTech lending market to the secured mortgage market, highlighting a broader and more impactful relationship. Third, [Dore and Mach \(2022\)](#) also show increased secured lending by Prosper borrowers, a finding close to my results. However, these results are not causal. My study builds on these results by providing causal evidence of the spillover effect from unsecured FinTech lending to secured mortgage lending.

My study contributes to the literature on credit market frictions by showing how FinTech lending in the small-ticket loan market can alleviate information frictions that borrowers face in larger, collateral-based loan markets. While some studies emphasize the role of cash-flow-based lending in addressing credit frictions ([Holmstrom and Tirole, 1997](#)), others demonstrate how collateral can reduce borrowing costs and increase credit limits ([Bernanke, Gertler, and Gilchrist, 1996](#); [Kiyotaki and Moore, 1997](#)). Recent research highlights the growing significance of cash-flow-based lending, with [Lian and Ma \(2021\)](#) documenting that nearly 80% of U.S. corporate loans are cash-flow-based, and [Benmelech, Kumar, and Rajan \(2020\)](#) observing a decline in secured lending. Thus, my finding that cash-flow-based lending can complement collateral-based lending is particularly relevant in today's lending landscape.

This paper is also related to the vast and growing literature that discusses the impact of FinTech lenders. Most of this literature focuses on the impact of FinTech lending within a given credit market. I contribute to this literature by providing causal evidence of impact of unsecured FinTech loan market to credit market outcomes in other secured credit markets. [Agarwal and Zhang \(2020\)](#), [Berg, Fuster, and Puri \(2022\)](#), [Allen, Gu, and Jagtiani \(2021\)](#), [Branzoli and Supino \(2020\)](#), and [Morse \(2015\)](#) provide excellent overview of frictions addressed by FinTech lenders. Specifically, use of alternative data for screening, superior screening algorithms, improved customer experience in terms of completely online application process and faster processing times, and innovative products for effective enforcement mechanisms, such as revenue-based financing, have helped FinTech lenders gain an edge over traditional lenders in unsecured personal credit lending ([Jagtiani and Lemieux, 2019](#); [Avramidis, Mylonopoulos, and Pennacchi, 2022](#); [Di Maggio et al., 2022](#); [Rajan and Xiong, 2024](#); [Vallee and Zeng, 2019](#)), small business lending ([Gopal and Schnabl, 2022](#); [Erel and Liebersohn, 2020](#); [Beaumont, Tang, and Vansteenberghe, 2021](#)) and the mortgage market ([Fuster, Plosser, Schnabl, and Vickery, 2019](#); [Buchak, Matvos, Piskorski, and Seru, 2018](#); [Fuster, Goldsmith-Pinkham, Ramadorai, and Walther, 2022](#)).

This paper is also related to the broad literature that records the role of innovation in financial intermediation to reduce information frictions in credit markets. The impact of digital payments is at the forefront of this literature as they help increase the economic outcomes of borrowers ([Dubey and Purnanandam, 2023](#); [Jack and Suri, 2014](#)) by alleviating information asymmetry for households and firms, resulting in relaxation of credit constraints ([Parlour, Rajan, and Zhu, 2022](#); [Ghosh, Vallee, and Zeng, 2022](#); [Björkegren and Grissen, 2018](#)).

The rest of the paper is organized as follows. Section 1 discusses data construction and descriptive statistics. Section 2 explains the results from the baseline ordinary least squares (OLS) specification. Section 3 explains the identification strategy, and discusses results using the standard difference-in-differences and the instrumented difference-in-differences

specifications. Section 4 presents potential economic mechanism, and presents results that support this mechanism. Section 5 discusses impact on mortgage loan performance due to unsecured FinTech lending. Section 6 discusses robustness tests to support my main results and mechanism. Section 7 concludes the paper.

1 Data and Descriptive Statistics

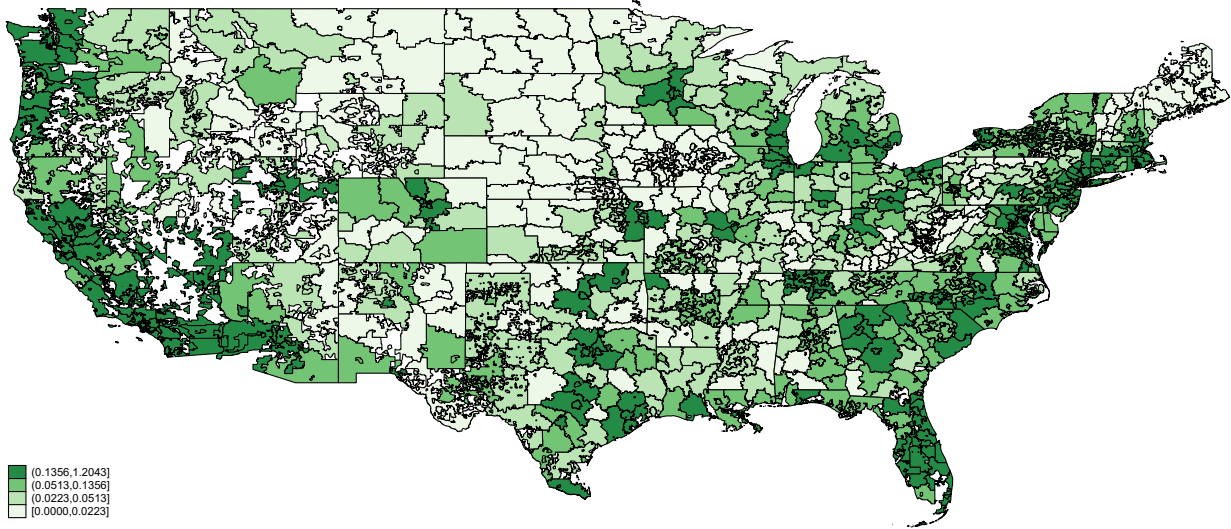
I construct the main sample to study the spillover effects from unsecured FinTech loan activity on mortgage activity using loan-level data by LendingClub and application-level data from HMDA. I aggregate this data at 3-digit zip code level, or zip3 level, where each zip3 is an area defined by all zip codes sharing the same first three digits. Consequently, a zip3 area serves as both the unit of observation and the level of treatment in the empirical setting of this paper. The sample here consists of 905 zip3 areas across 50 US states and the District of Columbia. Each zip3 area has a population of approximately 336,751, consistent with the typical population of a zip3 area in the U.S.

LendingClub Data: Figure 1 depicts the geographic variation of LendingClub’s loan activity in an area as a proportion of the total loan amount originated by LendingClub across the U.S. in a given year during the sample period. From 2010 to 2019, this dataset covers about 3 million loans. For each of these loans, I observe loan terms such as loan amount, interest rate, term period, purpose etc, reported income of the borrower, information about credit profile of the borrower such as their debt-to-income ratio, credit score etc, and employment details of the borrower. On average, LendingClub originated 335 loans in an area in a year.

As shown in Table 1, a typical personal loan from LendingClub has an average loan amount of \$14,047, an interest rate of 12.7%, and a term of either 3 or 5 years. Seventy percent of the loans in my sample were issued for a 3-year term, while the remaining 30%

Figure 1: Variation In LendingClub Loan Activity

Figure 1 presents the heatmap showing the average share of LendingClub’s unsecured personal loan amounts in each zip3 area as a percentage of the total LendingClub loan amount across the U.S. in a given year. The values represent the average of these percentages over the sample period from 2010 to 2019.



had a 5-year term. The average LendingClub borrower has an annual income of \$69,199. In terms of credit profile, the typical borrower has a FICO score of 696 and a debt-to-income ratio of 18.2%. Additionally, 80% of the LendingClub loans in my sample were taken out for the purpose of debt consolidation, specifically to refinance existing high-interest credit card debt and other unsecured loans at a lower cost.

HMDA Mortgage Data: To study mortgage activity in an area, I primarily use data reported by U.S. mortgage lenders under the Home Mortgage Disclosure Act (HMDA). This application-level data, provided annually by the Federal Financial Institutions Examination Council (FFIEC), represents the near universe of mortgage applications in the U.S. From 2010 to 2019, I observe approximately 155 million mortgage applications. For each application, I have information on the loan characteristics, such as the loan amount, type, and purpose, as well as the geographic location and some borrower characteristics, such as their reported income. Notably, the average income of a mortgage borrower in an area is \$90,480, which is higher than the average income of a LendingClub borrower, at \$69,199.

Table 2 shows that, on average, a zip3 area in the U.S. saw 17,095 mortgage applications per year during this period. Of these, about sixty-two percent, or 10,570 applications, resulted in a mortgage loan origination. The remaining applications were either withdrawn by the applicant, denied by the lender, or left incomplete. Of the total applications, thirty-nine percent, or 6,735, were for the purchase of a new home, while fifty-one percent, or 8,769, were for refinancing an existing mortgage. Seventy-one percent of new home purchase applications and fifty-seven percent of refinancing applications led to loan originations. The remaining applications were for home improvement purposes.

Moreover, I can observe the reasons for denial of a mortgage application by a lender for about 23 million out of nearly 28 million denied applications in my sample. The two main reasons for rejection are poor credit history and high debt-to-income ratios, accounting for 25.3% and 24.7% of these applications, respectively. The third most common reason, affecting 18.1% of the applications, is insufficient collateral, which often occurs when the house does not meet the lender's criteria.

Fannie Mae and Freddie Mac Mortgage Data: I now turn to a subsample of HMDA mortgage data, specifically loan-level data provided quarterly by Fannie Mae and Freddie Mac, to conduct pricing effect analysis as well as mortgage performance analysis that HMDA data alone cannot cover. From 2010 to 2019, this subsample consists of almost 36 million conforming mortgage loans and represents about forty percent of all mortgage loans reported under HMDA. For each loan in this dataset, I observe borrower characteristics such as credit score and debt-to-income ratio, as well as geographic location and loan characteristics, including loan amount, type, purpose, interest rate, and current delinquency status at a monthly frequency.

Table 3 shows that, on average 4,025 conforming mortgages are originated in a zip3 area in a year. Of these, forty two percent are for new home purchases, and fifty eight percent are for refinancing an existing mortgage. In contrast, in the main HMDA mortgage loan sample,

of the 10,570 mortgages originated on average in an area in a year, about forty five percent are for new home purchases and only forty seven percent are for refinancing. In terms of loan performance, on average in an area per year, 1.3% of mortgages experience a 30-day delinquency event within the first 12 months of origination, 2.2% within the first 24 months, and 3.0% within the first 36 months.

Mortgage FinTech Lenders Data: I use mortgage FinTech lenders classification data provided by [Buchak et al. \(2018\)](#) to conduct a robustness test in Section 6. This data allows me to identify mortgage activity generated by mortgage FinTech lenders in HMDA mortgage data during 2010 to 2019. Table 2 shows that on average, 1,824 such applications were processed per zip3 area per year, resulting in 1,077 loan originations.

2 Baseline Specification

I begin my analysis by estimating the following ordinary least squares (OLS) regression specification to check for correlations between FinTech lending activity and mortgage activity in an area for a given year.

$$Y_{z,t} = \beta_0 + \beta_1 \times \log(\text{No_LendingClub_Loans})_{z,t-k} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}; \quad k \in \{0, 1, 2\} \quad (1)$$

The response variable in this specification measures mortgage activity in area z in year t . Specifically, it refers to (a) the log of the number of mortgage applications and (b) the log of the number of mortgage loans originated in area z in year t . The main explanatory variable is the log of the number of LendingClub loans in area z in year $t - k$, where $k \in 0, 1, 2$. I use fixed effects, including zip3 area fixed effects captured by γ_z and the interaction of state and year fixed effects represented by $\phi_{z \times t}$. The inclusion of $\phi_{z \times t}$ precludes the need for year fixed effects. All standard errors are clustered at the zip3 level, as the intensity of treatment, or LendingClub loan activity, varies at this level. This approach is consistent with the clustering

methodology suggested by [Abadie, Athey, Imbens, and Wooldridge \(2023\)](#). The coefficient of interest, β_1 , captures the correlation between mortgage activity and LendingClub loan activity in an area in a given year.

Table 4 presents the regression results of the baseline specification. Columns (1), (2), and (3), provide the elasticity estimates of number of mortgage applications with respect to number of LendingClub loans in an area that capture the immediate effect, effect after one year, and effect after two years, respectively. Similarly, Columns (4), (5), and (6) offer elasticity estimates for the number of mortgage loans in an area. A key takeaway from this specification is that LendingClub loan activity is positively correlated with mortgage activity in an area. This correlation is statistically significant both immediately and with a lag of 1-2 years.

Another observation from the estimates in Table 4 is that the impact of LendingClub loan activity on mortgage activity in an area is largest in the immediate future and declines over time. Since it may take a few months for a borrower’s credit profile to update after taking out an unsecured LendingClub loan, the possibility of reverse causality cannot be fully ruled out. Additionally, these results could be influenced by unobserved factors, such as economic growth or opportunity in an area, which might simultaneously affect both LendingClub loan activity and mortgage activity, either immediately or in the future. In the next section, I discuss the identification strategy to address these concerns.

3 Identification

The results in the baseline OLS specification establish positive correlation between LendingClub loan activity and mortgage activity in an area. These results remain robust for lagged LendingClub loan activity in an area, largely eliminating the possibility of reverse causality. As described in specification (1), I employ zip3 area fixed effects to control for

time-invariant local characteristics and the interaction of state and year fixed effects to account for time-varying state-level regulatory or policy changes. This also precludes the effect due to any time-specific macroeconomic shocks to the economy. However, the declining trend of the spillover effect over time, as shown in Table 4, suggests potential identification concerns.

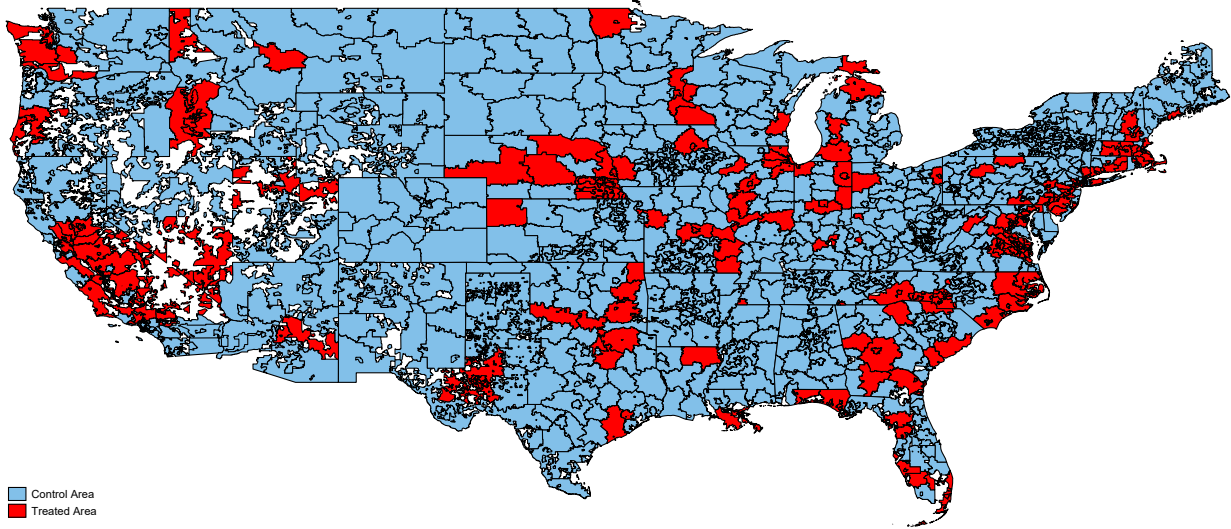
The key threat to identification in this setting is the possibility of time-varying, unobserved factors that could drive both LendingClub loan activity and current, as well as anticipated, mortgage activity in an area. Some examples include increased economic activity, a growing younger population, or increased access to mobile and internet services, all of which could boost demand for both LendingClub personal loans and mortgage loans. Another concern is that LendingClub may have expanded in certain areas specifically to capitalize on expected future mortgage activity. To address these challenges and establish a causal link, I leverage the February 2015 partnership between LendingClub and the BancAlliance network of community banks.

Established in 2010, the BancAlliance group is a national consortium of community banks that provides its member banks with access to lending resources to offer loan products that might otherwise be unavailable locally, administrative support for regulatory compliance, and opportunities to manage and diversify their portfolios through collaboration. Alliance Partners, a wholly owned subsidiary of Forbright Bank, serves as the asset manager for BancAlliance. At the time of its partnership with LendingClub in 2015, the network consisted of over 200 member banks across 39 states in the U.S. In order to better understand the scale of the BancAlliance network at the time, it is helpful to note that had all its member banks been one single bank, they would together have ranked fourth in the US by branch count and fourteenth by assets.

BancAlliance member banks partnered with LendingClub to invest in LendingClub's securitized loan offerings with the aim of diversifying their loan portfolios into consumer loans.

Figure 2: BancAlliance Network In 2015: Treated And Control Areas

Figure 2 highlights all areas where BancAlliance member banks operated in 2015 in red. These areas are defined as treated areas in the standard difference-in-differences regression design that I employ to identify the impact of LendingClub loan activity on mortgage activity. Of the 905 total zip3 areas, about 200 are treated and the remaining are control areas. It can be observed here that most treated areas have at most one BancAlliance member bank.



As part of this partnership, BancAlliance member banks also agreed to redirect their personal loan customers to the LendingClub platform. A typical BancAlliance member bank has a local presence and an asset size ranging from \$200 million to \$10 billion. As a result, when this partnership took effect in February 2015, it allowed LendingClub to expand its borrower base in areas where BancAlliance member banks operated. I use this quasi-exogenous variation in LendingClub loan activity to set up the test for identification.

I use a standard difference-in-differences regression design to test for identification. All areas where BancAlliance member banks operated in 2015 are defined as treated areas. The year in which the partnership between LendingClub and the BancAlliance group came into effect, i.e. 2015, is defined as the year of treatment. As a result, I test for impact on LendingClub loan activity and overall mortgage activity in treated areas post 2015 relative to control areas. Figure 2 highlights all treated areas, i.e., areas where at least one member bank of the BancAlliance network operated in Feb 2015. Of the 905 total zip3 areas in my sample, around 200 are treated areas and the remaining are control areas.

I make two identification assumptions in this setting. First, because LendingClub’s partnership with the BancAlliance network was established at the national level, LendingClub did not have the ability to selectively target specific areas for borrower expansion. Second, the member banks of the BancAlliance consortium are small community banks that sought to use this partnership to diversify into consumer loans. Moreover, Figure 2 shows that most areas had at most one member bank in 2015. Consequently, it is unlikely that these small banks could have leveraged their partnership with LendingClub to independently improve overall mortgage market outcomes in their areas. Based on these two assumptions, I consider the increase in LendingClub loan activity within treated areas as quasi-exogenous to overall mortgage activity and growth in these areas.

3.1 Impact On LendingClub Loan Activity

I first check for the importance of LendingClub’s partnership with the BancAlliance network using a standard difference-in-differences regression design as described in the following specification.

$$\begin{aligned} \log(\text{No_LendingClub_Loans})_{z,t} = & \pi_0 + \pi_1 \times \text{Treat}_z + \pi_2 \times \text{Post}_t \\ & + \pi_3 \times \text{Treat}_z \times \text{Post}_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t} \end{aligned} \tag{2}$$

The response variable in this specification is the log of the number of LendingClub loans in area z and year t . The main explanatory variable is the interaction between two indicator variables Treat and Post . Treat is 1 if area z is a treated area, and 0 otherwise. Post is 1 if year t is 2015 or later, and is 0 if year t is from 2010 to 2014. As a result, coefficient π_1 captures the impact on LendingClub loan activity in treated areas post 2015 versus control areas. I use zip3 area fixed effects, defined by γ_z , and the interaction of state and year fixed effects, denoted by $\phi_{z \times t}$. $\phi_{z \times t}$ precludes the need to control for year fixed effects separately. All standard errors are clustered at zip3 level, which is the level of treatment of my empirical

setting.

Figure 3 shows the year-wise results of this specification graphically. We observe here that LendingClub loan activity increases in treated areas after 2015 relative to control areas. Table 5 presents the results of specification (2), showing that in treated areas after 2015, the number of LendingClub loans increased by 9.25% compared to control areas. This results is statistically significant at 1% significance level. The results of this test confirm that the partnership between LendingClub and the BancAlliance network can be used as an instrument to establish a causal link between LendingClub loan activity and overall mortgage activity in an area.

3.2 Impact On Mortgage Activity

Next, I estimate the dynamic effects of LendingClub’s partnership with BancAlliance on the overall mortgage activity in an area. To do this, I first test for the parallel trends assumption using the specification (3).

$$Y_{z,t} = \delta_0 + \sum_k \delta_{t-k} \times Treat_z \times Post_{t-k} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t} \quad (3)$$

The response variable in this specification measures the mortgage activity in area z in year t . Specifically, it refers to (a) log of number of mortgage applications, and (b) log of number of mortgage loans originated in area z in year t . The main explanatory variable is the interaction between two indicator variables $Treat$ and $Post$. $Treat$ is 1 if area z is a treated area, and 0 otherwise. $Post$ is 1 if year t is 2015 or later, and is 0 if year t is from 2010 to 2014. As a result, the coefficients δ_{t-k} , where $k \in \{0, 1, 2\}$, provide the year-wise estimate of difference in mortgage activity in treated versus control areas. I use area fixed effects, defined by γ_z , and the interaction of state and year fixed effects, denoted by $\phi_{z \times t}$. $\phi_{z \times t}$ here precludes the need to separately control for year fixed effects. All standard errors

are clustered at zip3 level, which is the level of treatment.

Figure 4 presents the results of this specification. I show that, before 2015, mortgage activity, both in terms of the number of mortgage applications and the number of mortgage loans originated, in a treated area was not statistically different from that in a control area. After 2015, two key observations emerge. First, there is an immediate uptick in mortgage activity in treated areas compared to control areas. Second, the difference in mortgage activity between treated and control areas remains positive and statistically significant at the 95% confidence level each year after 2015. Note that Figure 4 shows the incremental effect of the instrument on mortgage activity in a treated area versus a control area for each year, rather than the cumulative effect.

Having established that no pre-trends exist in mortgage activity between treated and control areas, I now quantify the increase in mortgage activity in treated areas post 2015. I do this using a standard difference-in-differences regression design as described in the following specification.

$$Y_{z,t} = \delta_0 + \delta_1 \times Treat_z + \delta_2 \times Post_t + \delta_3 \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t} \quad (4)$$

The response variable $Y_{z,t}$ in this specification measures the mortgage activity in area z in year t . Specifically, it refers to (a) log of number of mortgage applications, and (b) log of number of mortgage loans originated in area z in year t . The coefficient of interest here is δ_1 , which captures the average impact on mortgage activity in treated areas post 2015. Table 6 presents the results of specification (4). I show that the number of mortgage applications increased by 2.97% and the number of mortgage loans increased by 3.02% in treated areas post 2015 relative to control areas. The coefficient values here are statistically significant at 5% significance interval.

So far, using two difference-in-difference specifications, I have established the following results. First, the partnership between LendingClub and the BancAlliance network in 2015

serves as a good instrument to establish a causal link between LendingClub loan activity and mortgage activity in an area. Second, there are no pre-trends in mortgage activity before 2015, while treated areas experience a statistically significant increase in mortgage activity after 2015. However, to further cement this causal link, I now check whether the increase in mortgage activity is specifically due to increase in LendingClub loan activity in treated areas post 2015, relative to control areas. I do this using the the instrumented difference-in-difference regression (DDIV) analysis.

$$Y_{z,t} = \beta_0 + \beta_1 \times \log(\widehat{No_LendingClub_Loans})_{z,t-k} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}; \quad k \in \{0, 1, 2\} \quad (5)$$

The response variable in this specification measures the mortgage activity in area z in year t . Specifically, it refers to (a) log of number of mortgage applications, and (b) log of number of mortgage loans originated in area z in year t . The main explanatory variable is the predicted values of the log of the number of LendingClub loans, constructed using coefficients estimated in the specification (2), which serves as the first stage of the DDIV analysis. In the second stage of DDIV in (5), the coefficient of interest, β_1 , captures the causal impact of LendingClub loan activity on mortgage activity in an area. I use zip3 fixed effects, defined by γ_z , and the interaction of state and year fixed effects, denoted by $\phi_{z \times t}$. $\phi_{z \times t}$ here precludes the need to separately control for year fixed effects. All standard errors are clustered at zip3 level, which is the level of treatment.

Table 7 presents the second stage regression estimates of the DDIV specification. Columns (1) - (3) provide elasticity estimates of the impact LendingClub loan activity on number of mortgage applications in an area in a year immediately, after a lag of one year, and after a lag of two years, respectively. Table 8 presents similar elasticity estimates for number of mortgage loans in an area. There are two important findings from the second-stage results. First, LendingClub loan activity has a positive and causal impact on mortgage activity in an area. The elasticity estimates, ranging from 30 to 40 basis points, are statistically significant at the

5% and 1% levels. Second, this spillover effect appears to be the lowest in the immediate term, increases a year and two later, and then eventually drops off. This is consistent with the expectation that improvements in the traditional credit metrics of a LendingClub borrower may take a few months to materialize.

3.3 Pricing Effect

Finally, I examine the impact of FinTech lenders on mortgage interest rates. If mortgage lenders are willing to supply more credit, the credit supply curve in the mortgage market should shift outward, leading to both an increase in the quantity of credit supplied and a decrease in loan prices for borrowers in equilibrium. To test this hypothesis, I use mortgage data provided by Fannie Mae and Freddie Mac, a subset of HMDA data comprising only conforming mortgages, which accounts for about 40% of all U.S. mortgages during my sample period, to construct mortgage market variables at zip3 level.⁶ Specifically, I use number of mortgage loans as well as average interest rate of mortgages in an area in a year as outcome variables in the specification (3). Figure 5 shows no pre-trends in mortgage loans or mortgage interest rates before 2015. However, after 2015, while the quantity of mortgage loans increased, mortgage rates declined in treated areas relative to control areas.

Conditional on an area having at least one conforming mortgage loan, Table 9 presents the effect of LendingClub loan activity on the quantity of mortgage loans in Column (1) and on the interest rate of these loans in Column (2), using specification (4). I find that in treated areas after 2015, the number of mortgages increased by 5.79% relative to control areas, while the mortgage interest rate declined by 1.62%. These results are statistically significant at the 1% level. This evidence confirms that an increase in unsecured LendingClub loan activity led not only to a rise in the number of mortgages in an area but also to a reduction in loan prices for borrowers. Consequently, this finding indicates that information

⁶I use Fannie Mae and Freddie Mac mortgage data to perform this analysis because HMDA mortgage data does not provide loan interest rates in my sample period from 2010 to 2019.

alleviation by LendingClub in the mortgage market led to an increase in credit supply from mortgage lenders.

Overall, the identification strategy presented in this section provides causal evidence of a positive spillover effect from unsecured LendingClub loan activity to mortgage activity in an area. The next section discusses the mechanism and potential tests to identify the source of this spillover effect.

4 Economic Mechanism

I now turn to the potential economic mechanism driving the spillover effect. A key explanation behind my findings is the alleviation of information frictions. By using alternative data and superior screening technology, FinTech lenders in the unsecured loan market can help overcome information frictions in the following two ways. First, they can facilitate borrowers to consolidate their high-cost, fragmented debt from multiple credit accounts into a single installment loan. Second, they can extend credit to new borrowers who have traditionally been underserved by conventional lenders. Both of these channels rely on FinTech lender's ability to actively screen borrowers and assess their repayment capacity, a process made more efficient through FinTech lender's access to enhanced borrower information set and superior processing technology.

During my sample period from 2010 to 2019, over 50% of mortgage applicants in HMDA mortgage data were rejected by lenders due to poor credit history or a high debt-to-income ratio. FinTech lenders in the unsecured loan market can help creditworthy borrowers overcome these information frictions by distinguishing them from higher-risk borrowers. After a creditworthy borrower receives a FinTech loan and uses it for debt consolidation, their repayment history and debt-to-income ratio should improve, eventually reflecting in their credit score. [Chava et al. \(2021\)](#) and [Balyuk \(2023\)](#) both document an increase in borrower

credit scores after receiving unsecured FinTech loans. Thus, FinTech lenders can enhance borrowers' traditional credit metrics, improving their access to the mortgage market. However, is the alleviation of information frictions truly the reason behind this spillover effect? To explore this question, I present two tests in this Section.

4.1 New Home Purchases Versus Refinancings

My first test is motivated by the fact that lenders should face greater information asymmetry in new home purchase mortgage activity rather than refinancing an existing mortgage. Consequently, I hypothesize that new home purchase mortgage activity in an area would be more sensitive to changes in LendingClub loans than refinancing mortgage activity. I test this hypothesis using mortgage data from 2010 to 2019 where approximately 39% of mortgage applications were for the purchase of a new home, 51% were for refinancing an existing mortgage, and the remaining 10% were for home improvement. I construct new home purchase and refinancing activity variables at the zip3 level and employ the following triple difference-in-differences regression design that helps me to estimate the differential impact of unsecured FinTech lending on new home purchase activity relative to refinancing mortgage activity.

$$\begin{aligned}
Y_{z,t,p} = & \beta_0 + \beta_1 \times Treat_z + \beta_2 \times Post_t + \beta_3 \times New_p + \beta_4 \times Treat_z \times Post_t \\
& + \beta_5 \times Post_t \times New_p + \beta_6 \times Treat_z \times New_p \\
& + \beta_7 \times Treat_z \times Post_t \times New_p + \lambda_{z \times p} + \phi_{z \times t} + \varepsilon_{z,t,p}
\end{aligned} \tag{6}$$

The response variable $Y_{z,t,p}$ measures mortgage activity in area z in year t for product type p , as measured by (a) the log of the number of mortgage applications and (b) the log of the number of mortgage loans originated. The main explanatory variable, which captures the impact of unsecured LendingClub loan activity on new home purchases versus refinancings, is an interaction term involving three indicator variables: $Treat_z$, $Post_t$, and New_p . $Treat_z$

and $Post_t$ are defined same as before. New_p is 1 if product type p represents a new home purchase and 0 if it represents refinancing. I use the interaction of zip3 and product type fixed effects, captured by $\lambda_{z \times p}$ to control for any time invariant local mortgage product characteristics, and the interaction of state and year fixed effects, represented by $\phi_{z \times t}$, to account for any time-varying state-level characteristics or any time-specific macroeconomic shocks. These fixed effects eliminate the need to separately use zip3 and year fixed effects. All standard errors are clustered at the zip3 level, which is the level of treatment.

The coefficient of interest, β_7 , captures the average differential impact on mortgage activity in a treated area versus a control area for a new home purchase compared to refinancing, after 2015. Table 10 presents the triple differences estimates of this specification. I show that in treated areas after 2015, new home purchase applications increased by 3.46%, and new home purchase mortgage originations grew by 4.65%, versus refinancings and control areas. These estimates are statistically significant at 10% and 5% levels, respectively. This finding is consistent with the information alleviation mechanism described above.

4.2 Middle-Income Borrowers

In my second test, I exploit the variation in information asymmetry across borrowers. Specifically, I test whether the spillover effect varies across borrowers in different income bands. This test is motivated by the idea that middle-income borrowers stand to benefit the most from improved information processing and advanced screening. Low income borrowers are less likely to benefit, as better screening would generally reveal them as higher risk. Similarly, high income borrowers are also unlikely to gain significantly, since they are typically identified as low risk. It is the middle-income group where a mix of both good and bad types likely exists, making them the most likely to benefit from improved information processing.

Furthermore, if FinTech lenders in the unsecured personal loan market do not alleviate information frictions as the proposed mechanism suggests, it could be argued that they

primarily help all borrowers gain access to cheap debt consolidation loans, which may eventually benefit them in the mortgage market. In this scenario, one would expect low-income individuals to be the most responsive to the penetration of unsecured FinTech lending in their area.

To test this hypothesis, I construct mortgage activity and LendingClub loan variables for six income subgroups at zip3 level and employ the following two specifications. First, I use a triple differences analysis to examine the differential impact on borrower income bands in treated areas after the 2015 partnership between LendingClub and BancAlliance, compared to control areas and other income bands. Second, I separately assess the sensitivity of each income subgroup to unsecured LendingClub loan activity using a difference-in-differences regression analysis.

4.2.1 Triple Differences

In this specification, I use the following triple differences regression design to study the impact of LendingClub loan activity on mortgage activity in an area across income bands.

$$\begin{aligned}
Y_{z,t,b} = & \beta_{0,b} + \beta_{1,b} \times Treat_z + \beta_{2,b} \times Post_t + \beta_{3,b} \times IncBand_b + \beta_{4,b} \times Treat_z \times Post_t \\
& + \beta_{5,b} \times Post_t \times IncBand_b + \beta_{6,b} \times Treat_z \times IncBand_b \\
& + \beta_{7,b} \times Treat_z \times Post_t \times IncBand_b + \lambda_{z \times b} + \phi_{z \times t} + \varepsilon_{z,t,b}
\end{aligned} \tag{7}$$

The response variable $Y_{z,t,b}$ measures mortgage activity in area z in year t for borrower income band b , as measured by (a) the log of the number of mortgage applications, (b) the log of the number of mortgage loans, (c) the log of the number of new mortgage applications, (d) the log of the number of new mortgage loans, (e) the log of the number of mortgage refinancing applications, and (f) the log of the number of mortgage refinancing loans. The main explanatory variable for each response variable and for each income band is the interaction of three indicator variables: $Treat_z$, $Post_t$, and $IncBand_b$. $Treat_z$ and $Post_t$ are as defined

earlier. $IncBand_b$ is 1 if an individual is within the income band b and 0 otherwise. I use six income bands, namely $< \$40K$, $\$40K - \$60K$, $\$60K - \$80K$, $\$80K - \$100K$, $\$100K - \$120K$, and $> \$120K$. I use the interaction of zip3 and income band fixed effects, captured by $\lambda_{z \times b}$ to control for any time invariant local characteristics of borrowers in an income band, and the interaction of state and year fixed effects, represented by $\phi_{z \times t}$, to account for any time-varying state-level characteristics or any time-specific macroeconomic shocks. These fixed effects eliminate the need to separately use zip3 and year fixed effects. All standard errors are clustered at the zip3 level, which is the level of treatment.

The coefficient of interest, $\beta_{7,b}$, captures the average differential impact on mortgage activity in a treated area versus a control area for borrowers in income band b relative to those in other income bands, after 2015. Table 11 presents the triple differences estimates of this specification. I show that in treated areas after 2015, mortgage activity of middle income individuals is most responsive to changes in unsecured LendingClub activity in their area, versus borrowers in other income bands and control areas. Specifically, I observe that, conditional on applying for a mortgage, individuals with incomes between \$60,000 and \$80,000 are the most sensitive to LendingClub loan activity in their area. These estimates are statistically significant at 1% levels.

4.2.2 Difference-In-Differences Across Income Bands

In this specification, I employ the following difference-in-differences regression design for each mortgage activity variable across the six income band subgroups, as defined earlier.

$$Y_{z,t,b} = \beta_0 + \beta_{1,b} \times Treat_z + \beta_{2,b} \times Post_t + \beta_{3,b} \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t,b} \quad (8)$$

The response variable $Y_{z,t,b}$ measures mortgage activity in area z in year t for borrower income band b , as measured by (a) the log of the number of mortgage applications, (b) the log of the number of mortgage loans, (c) the log of the number of new mortgage applications,

(d) the log of the number of new mortgage loans, (e) the log of the number of mortgage refinancing applications, and (f) the log of the number of mortgage refinancing loans. The main explanatory variable here is the interaction of indicator variables $Treat_z$ and $Post_t$.

The main coefficient of interest here is $\beta_{7,b}$, which captures the average impact on mortgage activity in treated areas post 2015 for the subgroup of income band b . Figure 6 presents the point estimates of this exercise graphically. As shown in the figure, middle-income individuals are the most sensitive to changes in unsecured LendingClub loan activity in their area across all measures of mortgage activity. Specifically, I observe that, conditional on applying for a mortgage, individuals with incomes between \$60,000 and \$80,000 are the most sensitive to LendingClub loan activity in their area. The standard errors of the point estimates plotted here are presented in Tables 12 and 13 for mortgage applications and loans, respectively, with the remaining results in the Appendix.

These results suggest that middle-income borrowers, who are in the income band where good and bad types are most likely pooled together, are more likely to benefit from the spillover effect. In contrast, both low-income and high-income borrowers, where information asymmetry is likely lower, are unlikely to benefit from this spillover effect.

5 Mortgage Performance

In this Section, I test whether the new mortgage originations facilitated by unsecured FinTech lenders are riskier than average. If mortgage delinquencies increase disproportionately relative to mortgage loan originations, it could be argued that unsecured FinTech lenders such as LendingClub were unable to identify creditworthy borrowers and alleviate information frictions in the mortgage market. To test this hypothesis, I use mortgage performance data provided by Fannie Mae and Freddie Mac to construct mortgage and delinquency variables at the zip3 level. I then conduct the analysis in two stages using an instrumented

difference-in-differences (DDIV) approach.

In the first stage, I use the standard difference-in-differences design as described in specification (4). Table 14 shows the estimate from this specification in Column (1). I find that in treated areas after 2015, the number of mortgages increased by 5.55%, relative to control areas. This result is statistically significant at 1% level. These results confirm that increase in unsecured LendingClub loan activity resulted in increase in the number of mortgages in an area. Furthermore, this finding shows that the spillover effect is also present in the Fannie Mae and Freddie Mac mortgage data, which is a subset of the main HMDA mortgage data.

Next, I test for change in mortgage delinquencies specifically due to increase in mortgages in an area using the following instrumented difference-in-differences specification.

$$\begin{aligned} \log(\text{No_Mortgage_Delinquencies})_{z,t,t+k} = & \beta_0 + \beta_1 \times \log(\widehat{\text{No_Mortgages}})_{z,t} + \gamma_z \\ & + \phi_{z \times t} + \varepsilon_{z,t}; \quad k \in \{1, 2, 3\} \end{aligned} \quad (9)$$

The response variable here is the log of the number of mortgage delinquencies in area z from year t to year $t + k$, where $k \in \{1, 2, 3\}$. The main explanatory variable is the predicted values of the log of the number of mortgages in an area constructed using the estimate presented in Column (1) in Table 14.

The estimates of the DDIV specification are presented in Table 14 in Columns (2) - (4). I show that a one percent increase in mortgage loans led to 0.73% increase in 30-day delinquency events within 12 months of mortgage originations, and about a 1.00% increase in delinquency events within 24 and 36 months of mortgage originations in an area. These results show that mortgage delinquencies do not grow disproportionately relative to the increase in mortgages facilitated by unsecured LendingClub loan activity in an area.

The fact that new mortgage originations are not riskier than average suggests that LendingClub effectively used alternative data and superior processing technology to identify

creditworthy borrowers for debt consolidation loans, ultimately increasing their access to the mortgage market.

6 Robustness Tests

In this section, I present results from two robustness tests that further support my main findings and proposed economic mechanism.

6.1 Removing FinTech Mortgage Lenders

In the first test, I replicate the exercise from Sections 2 and 3, this time excluding all mortgage applications and loans processed by FinTech lenders in the mortgage market. FinTech lenders are known to process applications more quickly than traditional lenders and tend to specialize in refinancing activity (Fuster et al., 2019). However, there are concerns that the increase in unsecured FinTech loan activity may directly support the activity generated by mortgage FinTech lenders. To address this, I use the list of FinTech mortgage lenders from 2010 to 2019 provided by Buchak et al. (2018), remove all mortgage applications and loans processed by these lenders from my main HMDA mortgage sample, and re-run the baseline OLS as well as the DDIV analysis.

The results of this exercise are as follows. Table 19 shows the results of the baseline specification (1) for all non-FinTech mortgage lenders. I find that, on average, a one percent increase in LendingClub loan activity resulted in a 7 basis points increase in mortgage activity. Figure 9 shows no pre-trends in mortgage activity before 2015, while mortgage applications and loans increased in treated areas relative to control areas after 2015. Using a standard difference-in-differences analysis similar to specification (4), I show in Table 20 that mortgage applications increase by 2.65%, and mortgage loans increase by 2.59% in treated areas after 2015, relative to control areas. These estimates are both statistically significant at the 5%

significance level.

Finally, using DDIV approach as in specification (5), I show in Table 21 that a one percent increase in LendingClub loans resulted in a 0.27% increase in mortgage applications immediately, a 0.35% increase after one year, and a 0.26% increase after two years. These estimates are statistically significant. Table 22 presents similar results for mortgage loans in an area.

Overall, this robustness test shows that an increase in unsecured FinTech loan activity, such as LendingClub loans, led to higher mortgage activity in an area, even when all mortgage activity generated by FinTech mortgage lenders is excluded from the sample. This suggests that my results are not solely driven by FinTech mortgage lenders learning from information uncovered by FinTech lenders in the unsecured loan market.

6.2 Fannie Mae And Freddie Mac Mortgage Data

In the second test, I replicate the exercise from Sections 2 and 3, this time using mortgage loan data provided by Fannie Mae and Freddie Mac. The pricing effect findings in Section 3 and the delinquency findings in Section 6 rely solely on this dataset to demonstrate both an outward shift in the credit supply curve in the mortgage market and that new mortgages facilitated by unsecured LendingClub loan activity are not riskier than average. As a result, I perform this test to check whether my main findings hold in this dataset as well. I construct the mortgage loan variables at the zip3 level using this dataset and re-run both the baseline OLS and DDIV analyses.

The results of this exercise are as follows. Table 23 shows the results of the baseline specification (1) for all non-FinTech mortgage lenders. I find that, on average, a one percent increase in LendingClub loan activity resulted in about a 7 basis points increase in mortgage activity. However, this effect is not significant after two years, unlike in the main HMDA mortgage dataset. Figure 5a shows no pre-trends in mortgage loans before 2015, while they

increased in treated areas relative to control areas after 2015. Using a standard difference-in-differences analysis similar to specification (4), I show in Table 24 that mortgage loans increase by 5.55% in treated areas after 2015, relative to control areas. This result is statistically significant at 1% level.

Finally, using DDIV approach as in specification (5), I show in Table 25 that a one percent increase in LendingClub loans resulted in a 0.55% increase in mortgage applications immediately, a 0.56% increase after one year, and a 0.37% increase after two years. These estimates are statistically significant at 5% and 10% level.

Overall, this robustness test shows that an increase in unsecured FinTech loan activity, such as LendingClub loans, led to higher mortgage loans in an area, even when using only the Fannie Mae and Freddie Mac mortgage dataset.

7 Conclusion

In this paper, I provide causal evidence that unsecured FinTech lending improves borrower outcomes in other secured credit markets. Specifically, I find that increase in LendingClub loans in an area led to an increase in mortgage lending in that area. To establish causality, I employ a novel identification strategy based on LendingClub’s partnership with the BancAlliance consortium of community banks in February 2015. This provides a source of quasi-exogenous variation in LendingClub loan activity, as BancAlliance member banks redirected their personal loan customers to the LendingClub platform. I classify three-digit zipcode areas in the US as treated or control areas depending on whether a BancAlliance member bank operated in that area in 2015. I find that both LendingClub and mortgage activity increased in treated areas versus control areas after 2015. Additionally, I demonstrate that this increase in mortgage activity is specifically driven by the rise in LendingClub loan activity.

My findings suggest that the key driver of the spillover effect of unsecured Fintech loans on secured mortgage loans is alleviation of information asymmetry by FinTech lenders. This conclusion is supported by three key findings. First, new home purchase activity, where information frictions are typically larger, is more sensitive to unsecured FinTech loan activity than refinancings. Second, mortgage applicants facing higher information frictions, such as middle-income individuals, respond more strongly to unsecured FinTech lending. Third, I find that mortgage default rates do not increase despite the rise in mortgage lending. This result indicates that FinTech lenders have the ability to effectively identify and assist creditworthy borrowers who were previously on the verge of accessing the mortgage market but lacked the necessary credit profile to do so.

Given the recent rise of FinTech lending in the unsecured loan market, and the fact that we are still in the early stages of designing a regulatory framework for these lenders, my study carries important implications for millions of borrowers in this market. I show that unsecured FinTech lenders can alleviate credit constraints for borrowers, even in larger, secured credit markets, such as the mortgage market.

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Figure 3: LendingClub Loan Activity In Treated Versus Control Areas

$$\log(\text{No_LendingClub_Loans})_{z,t} = \pi_0 + \pi_1 \times \text{Treat}_z + \pi_2 \times \text{Post}_t + \pi_3 \times \text{Treat}_z \times \text{Post}_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

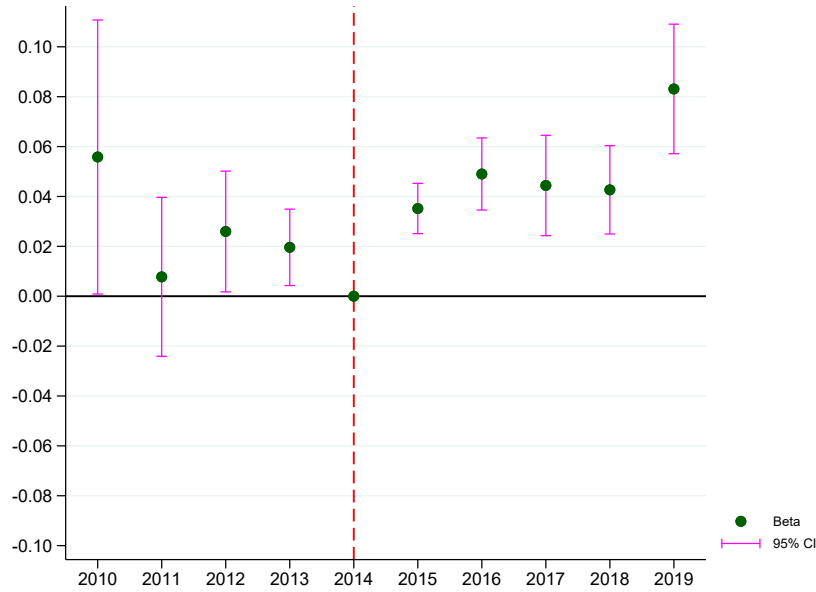
Figure 3 shows the difference in LendingClub loan activity in treated areas versus control areas, before and after 2015. I plot here the difference between the average of the log of LendingClub number of loans in treated and control areas in a given year. I employ area, and the interaction of state and year fixed effects. All standard errors are clustered at area level, which is the level of treatment. In this figure I show that LendingClub loan activity increased significantly in treated areas after 2015, versus control areas.



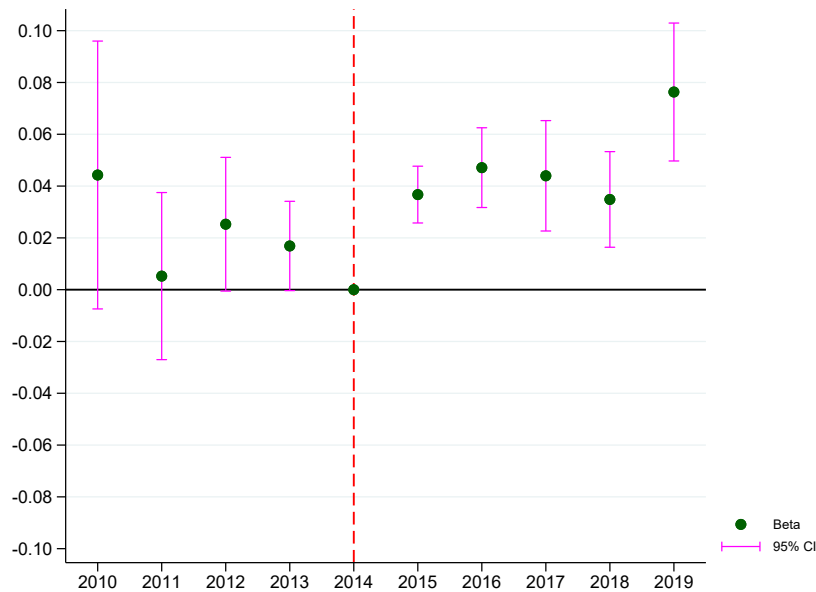
Figure 4: Impact Of LendingClub’s Partnership With BancAlliance On Mortgage Activity

$$Y_{z,t} = \delta_0 + \sum_k \delta_{t-k} \times Treat_z \times Post_{t-k} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

Figure 4 presents the year-wise point estimates demonstrating the impact of LendingClub’s partnership with the BancAlliance network in 2015 on mortgage activity, as measured by number of applications and loan originations. I employ area, and the interaction of state and year fixed effects. All standard errors are clustered at area level, which is the level of treatment. In this figure, I show that mortgage activity was similar in treated areas versus control areas before 2015. Moreover after 2015, treated areas saw increased mortgage activity.



(a) Year-wise Estimates of Mortgage Applications in Treated Versus Control Areas

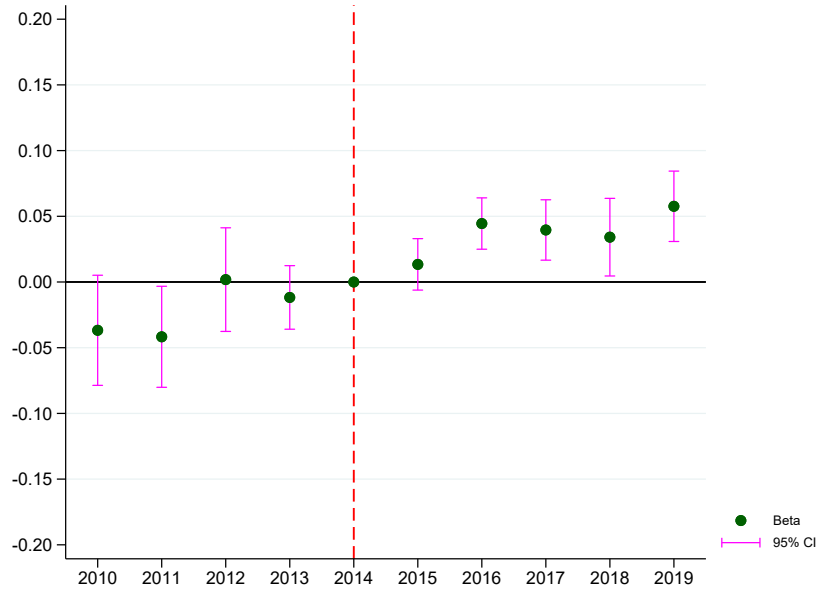


(b) Year-wise Estimates of Mortgage Loans in Treated Versus Control Areas

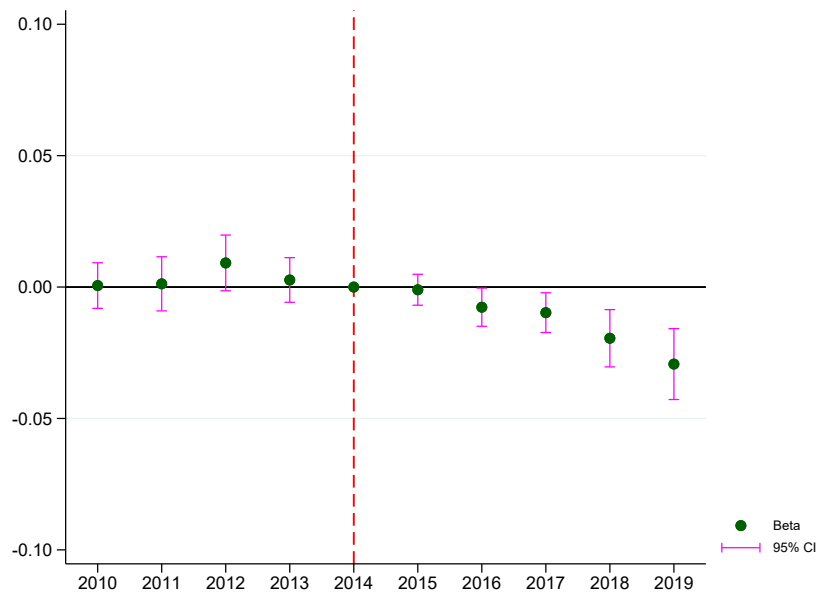
Figure 5: Pricing Effect: Impact On Mortgage Loans And Rates

$$Y_{z,t} = \delta_0 + \sum_k \delta_{t-k} \times Treat_z \times Post_{t-k} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

Figure 5 plots the year-wise point estimates demonstrating the impact of LendingClub’s partnership with the BancAlliance network in 2015 on mortgage activity, using mortgage data provided by Fannie Mae and Freddie Mac. I employ zip3, and the interaction of state and year fixed effects. All standard errors are clustered at zip3 level, which is the level of treatment. The results show that mortgage activity was similar in treated versus control areas before 2015. Moreover after 2015, treated areas experienced an increase in the quantity of mortgage loans and a decline in mortgage rates compared to control areas. Together, these findings provide evidence that LendingClub loan activity, as instrumented by its partnership with the BancAlliance group, shifted the credit supply curve outward in the mortgage market.



(a) Year-wise Estimates of Mortgage Loans in Treated Versus Control Areas

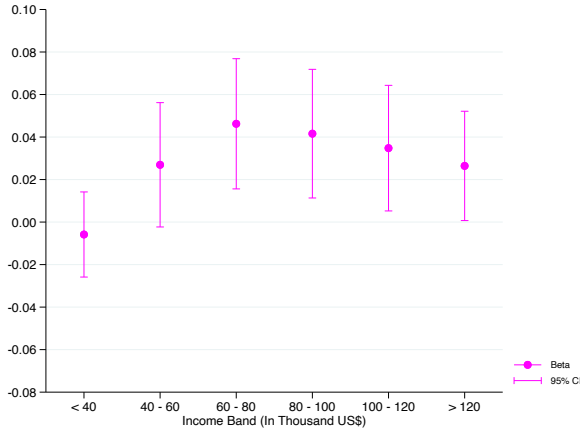


(b) Year-wise Estimates of Mortgage Rates in Treated Versus Control Areas

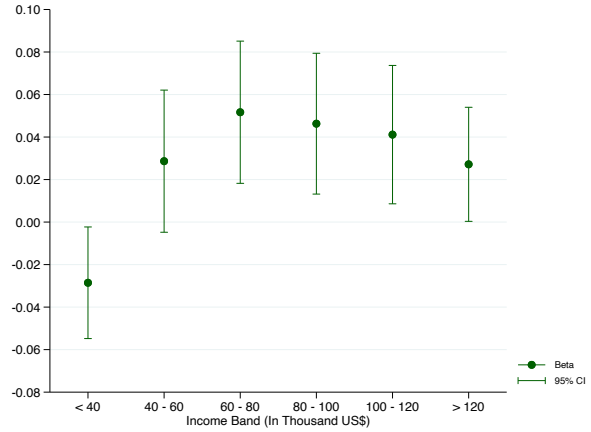
Figure 6: Impact On Mortgage Activity Across Income Bands

$$Y_{z,t,b} = \beta_0 + \beta_{1,b} \times Treat_z + \beta_{2,b} \times Post_t + \beta_{3,b} \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t,b}$$

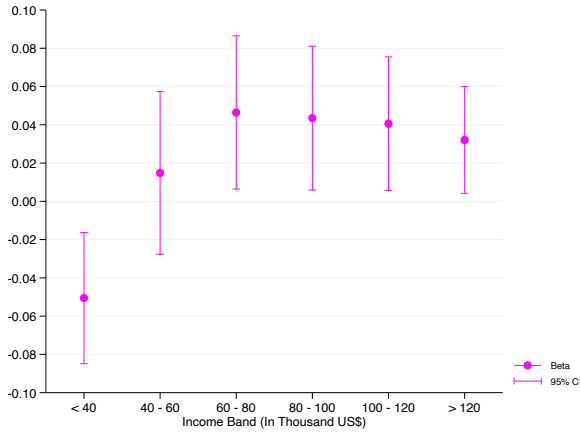
Figure 6 presents the difference-in-differences estimates demonstrating the impact of unsecured LendingClub loan activity on mortgage activity across income bands. Table 12 and Table 13 display these estimates for all mortgage applications and loans, with the remaining estimates provided in the Appendix. I employ zip3, and the interaction of state and year fixed effects in the subsample of each income band. All standard errors are clustered at zip3 level. This figure shows that middle-income borrowers in the mortgage market are the most responsive to changes in unsecured LendingClub loan activity in their area.



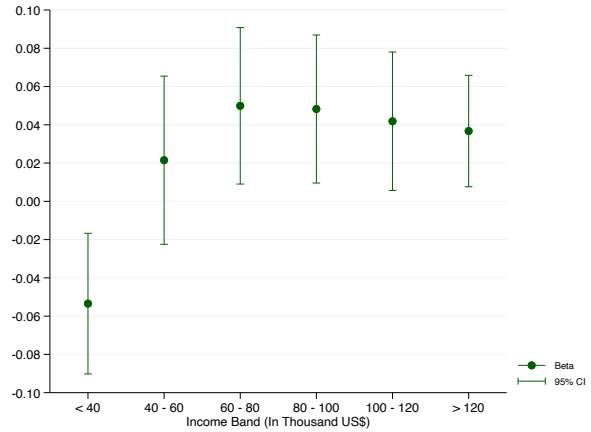
(a) All Mortgage Applications



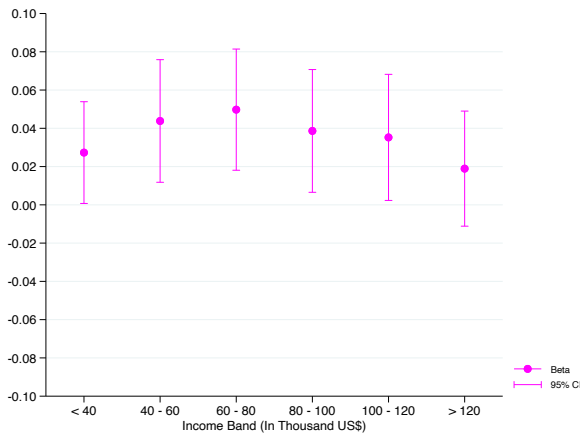
(b) All Mortgage Loans



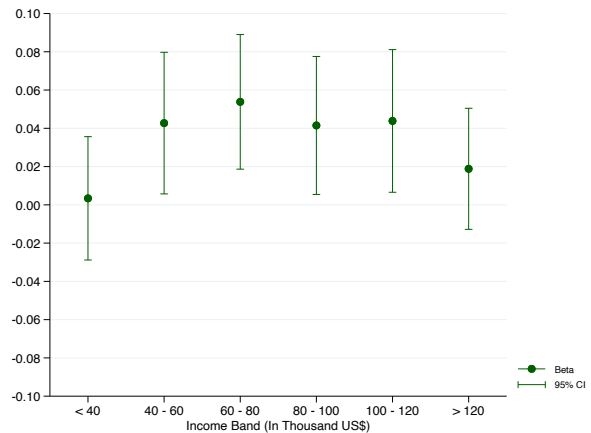
(c) New Mortgage Applications



(d) New Mortgage Loans



(e) Refi Mortgage Applications



(f) Refi Mortgage Loans

Table 1: Descriptive Statistics: LendingClub Loan And Borrower Characteristics

Table 1 presents the descriptive statistics of LendingClub loan and borrower characteristics. These statistics are shown at the zip3 level, which is the unit of sampling in my analysis. The sample period is from 2010 to 2019.

	N	Mean	SD	Min	P25	P50	P75	Max
Loan Amount (USD)	8,278	14,047	2,679	1,250	13,077	14,417	15,541	35,000
Median Int Rate (%)	8,278	12.70	1.46	5.32	11.99	12.62	13.53	23.63
Median DTI (%)	8,278	18.16	3.36	0.00	16.44	18.62	20.26	56.72
Median FICO	8,278	696	14	660	690	695	700	795
Number of Loans	8,278	335	564	1	33	131	367	5,364
Borrower Income (USD)	8,278	69,199	13,660	15,000	61,801	68,126	75,488	205,169

Table 2: Descriptive Statistics: Mortgage Applications And Loans

Table 2 presents the descriptive statistics of mortgage applications and loans. The statistics are shown at the zip3 level, which is the unit of observation of my analysis. The sample period is from 2010 to 2019. This data is reported by mortgage lenders under the Home Mortgage Disclosure Act (HMDA).

	N	Mean	SD	P25	P50	P75	Max
All Mortgage Apps	9,034	17,095	23,170	3,616	8,830	21,082	305,952
All Mortgage Loans	9,034	10,570	14,405	2,192	5,487	12,975	194,259
New Mortgage Apps	9,034	6,735	9,689	1,363	3,339	8,057	119,107
New Mortgage Loans	9,034	4,798	6,922	923	2,358	5,760	84,279
Refi Mortgage Apps	9,034	8,769	12,276	1,694	4,419	10,586	181,780
Refi Mortgage Loans	9,034	4,991	7,341	916	2,401	5,887	115,789
FinTech Mortgage Apps	9,034	1,824	4,604	201	536	1,494	112,644
FinTech Mortgage Loans	9,034	1,077	2,711	110	304	894	70,921
Applicant Income (USD)	9,034	90,480	30,468	72,754	82,035	96,763	435,407
Loan Amount (USD)	9,034	167,569	92,496	110,464	137,776	188,292	884,499
Population	9,034	336,751	368,346	109,860	207,338	428,341	2,975,626

Table 3: Descriptive Statistics: Fannie Mae and Freddie Mac Mortgage Loans

Table 3 presents the descriptive statistics of conforming mortgage loans. The statistics are shown at the zip3 level, which is the unit of observation of my analysis. The sample period is from 2010 to 2019. This data is provided by Fannie Mae and Freddie Mac.

	N	Mean	SD	Min	P25	P50	P75	Max
All Mortgage Loans	8,875	4,025	5,649	1	713	1,968	4,903	80,448
New Mortgage Loans	8,875	1,698	2,412	0	285	797	2,042	26,123
Refi Mortgage Loans	8,875	2,326	3,716	0	375	1,018	2,682	67,270
Delinquencies Within 12mths	8,875	53	98	0	8	22	58	1,751
Delinquencies Within 24mths	8,875	94	153	0	15	41	107	2,305
Delinquencies Within 36mths	8,875	125	193	0	21	56	145	2,477
Loan Amount (USD)	8,875	187,214	67,758	50,000	142,200	169,534	209,544	959,000
Loan-To-Value (%)	8,875	73.85	5.83	34.93	70.86	74.92	77.71	121.90
Median Credit Score	8,875	763	12	591	756	763	771	818
Median DTI (%)	8,872	33.35	2.91	14.00	31.00	33.00	35.00	50.00

Table 4: Baseline OLS: Impact On Mortgage Market Activity

$$Y_{z,t} = \beta_0 + \beta_1 \times \log(\text{No_LendingClub_Loans})_{z,t-k} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}; \quad k \in \{0, 1, 2\}$$

Table 4 presents the key regression estimates where the response variable is the log of number of mortgage applications in Columns (1), (2), and (3), and the log of number of mortgage loans in Columns (4), (5), and (6) in area z in year t . The main explanatory variables are the log of number of LendingClub loans in area z in year $t - k$, where $k \in \{0, 1, 2\}$. The sample here is from 2010 to 2019. I employ zip3, and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. This table shows that LendingClub loan activity is positively correlated with overall mortgage activity in an area.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Apps	Log Apps	Log Apps	Log Loans	Log Loans	Log Loans
Log LC Loans	0.0759*** (0.0098)			0.0768*** (0.0096)		
Log LC Loans.L1		0.0589*** (0.0070)			0.0560*** (0.0072)	
Log LC Loans.L2			0.0481*** (0.0070)			0.0471*** (0.0072)
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	7,223	7,223	7,223	7,223	7,223	7,223
Adj R-squared	0.0355	0.0364	0.0348	0.0316	0.0285	0.0289
Number of Zip3s	904	904	904	904	904	904

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Difference-in-Differences: Impact On LendingClub Loans

$$\log(\text{No_LendingClub_Loans})_{z,t} = \pi_0 + \pi_1 \times \text{Treat}_z + \pi_2 \times \text{Post}_t + \pi_3 \times \text{Treat}_z \times \text{Post}_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

Table 5 presents the key regression estimate where the response variable is the log of number of LendingClub loans in area z in year t . The main explanatory variable is the interaction of dummy variables Treat_z and Post_t . Treat_z is 1 if area z is a treated area, i.e., it housed a member bank of the BancAlliance network in 2015, as shown in Figure 2. It is 0 otherwise. Post_t is 1 if year t is 2015 or later, and 0 if earlier. The sample here is from 2010 to 2019. I employ zip3 and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. This table shows the increase in LendingClub loan activity in treated versus control areas after its partnership with the BancAlliance group in 2015.

	(1)
	Log No of LendingClub Loans
Treat X Post	0.0925*** (0.0317)
Zip3 FE	Yes
State X Year FE	Yes
Number of Observations	9,034
Number of Zip3s	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: Difference-in-Differences: Impact on Mortgage Applications And Loans

$$Y_{z,t} = \delta_0 + \delta_1 \times Treat_z + \delta_2 \times Post_t + \delta_3 \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

Table 6 presents the key regression estimates where the response variable is the log of number of mortgage applications in Column (1) and log of number of mortgage loans in Column (2) in area z in year t . The main explanatory variable is the interaction of dummy variables $Treat_z$ and $Post_t$. $Treat_z$ is 1 if area z is a treated area, i.e., it housed a member bank of the BancAlliance network in 2015, as shown in Figure 2. It is 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 if earlier. The sample here is from 2010 to 2019. I employ zip3 and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. This table shows that mortgage activity increased significantly in treated areas after 2015 relative to control areas.

	(1)	(2)
	Log Mortgage Apps	Log Mortgages
Treat X Post	0.0297** (0.0123)	0.0302** (0.0127)
Zip3 FE	Yes	Yes
State X Year FE	Yes	Yes
Number of Observations	9,033	9,033
Number of Zip3s	905	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Instrumented Difference-in-Differences: Impact On Mortgage Applications

$$1^{st} \text{ Stage: } \log(\text{No_LendingClub_Loans})_{z,t} = \pi_0 + \pi_1 \times \text{Treat}_z + \pi_2 \times \text{Post}_t + \pi_3 \times \text{Treat}_z \times \text{Post}_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

$$2^{nd} \text{ Stage: } \log(\text{No_Mortgage_Apps})_{z,t+k} = \beta_0 + \beta_1 \times \log(\widehat{\text{No_LendingClub_Loans}})_{z,t} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}; \quad k \in \{0, 1, 2\}$$

Table 7 presents the key regression estimates from the second stage of the instrumented difference-in-differences (DDIV) regression estimates. The response variable in this stage is the log of the number of mortgage applications in area z in year t . The main explanatory variable is the predicted values of the log of the number of LendingClub loans constructed using coefficients obtained in the first stage, as shown in Table 5. The sample here is from 2010 to 2019. I employ zip3 and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides causal evidence to show that mortgage applications increased due to increase in the number of LendingClub loans in an area.

	(1)	(2)	(3)
	Log Apps.T	Log Apps.T+1	Log Apps.T+2
Log LC Loans	0.3067** (0.1462)	0.4022*** (0.1414)	0.3434*** (0.1187)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	9,033	8,127	7,223
Number of Zip3s	905	904	904

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: Instrumented Difference-in-Differences: Impact On Mortgage Loans

$$1^{st} \text{ Stage: } \log(\text{No_LendingClub_Loans})_{z,t} = \pi_0 + \pi_1 \times \text{Treat}_z + \pi_2 \times \text{Post}_t + \pi_3 \times \text{Treat}_z \times \text{Post}_t \\ + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

$$2^{nd} \text{ Stage: } \log(\text{No_Mortgage_Loans})_{z,t+k} = \beta_0 + \beta_1 \times \log(\widehat{\text{No_LendingClub_Loans}})_{z,t} + \gamma_z + \phi_{z \times t} \\ + \varepsilon_{z,t}; \quad k \in \{0, 1, 2\}$$

Table 8 presents the key regression estimates of the second stage of the instrumented difference-in-differences (DDIV) regression estimates. The response variable in this stage is the log of the number of mortgage loans in area z in year t . The main explanatory variable is the predicted values of the log of the number of LendingClub loans constructed using coefficients obtained in the first stage, as shown in Table 5. The sample here is from 2010 to 2019. I employ zip3 and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides causal evidence to show that mortgage loan originations increased due to increase in the number of LendingClub loans in an area.

	(1)	(2)	(3)
	Log Loans.T	Log Loans.T+1	Log Loans.T+2
Log LC Loans	0.3119** (0.1508)	0.3664*** (0.1413)	0.2972** (0.1188)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	9,033	8,127	7,223
Number of Zip3s	905	904	904

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 9: Pricing Effect: Difference-in-Differences - Impact on Mortgage Rates

$$Y_{z,t} = \delta_0 + \delta_1 \times Treat_z + \delta_2 \times Post_t + \delta_3 \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

Table 9 presents the regression estimates where the response variable is the mortgage interest rate in area z in year t . This variable is constructed using conforming mortgage data provided by Fannie Mae and Freddie Mac, which represents a subset of overall mortgage data, comprising about 40% of all mortgages. The main explanatory variable is the interaction of dummy variables $Treat_z$ and $Post_t$. $Treat_z$ is 1 if area z is a treated area, i.e., it housed a member bank of the BancAlliance network in 2015, as shown in Figure 2. It is 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 if earlier. The sample period is from 2010 to 2019. I employ zip3 and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. This table shows that, conditional on at least one conforming mortgage in an area in a year, while FinTech lending increases mortgage originations, it also leads to lower mortgage interest rates. This suggests that FinTech lenders facilitate an increase in mortgage originations via an outward shift in the credit supply curve in the mortgage market.

	(1) Log Mortgages	(2) Mortgage Rate
Treat X Post	0.0579*** (0.0183)	-0.0162*** (0.0037)
Zip3 FE	Yes	Yes
State X Year FE	Yes	Yes
Number of Observations	8,862	8,862
Number of Zip3s	892	892

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 10: Triple Differences: Impact on New Home Purchase Vs Refinancing Activity

$$Y_{z,t,p} = \beta_0 + \beta_1 \times Treat_z + \beta_2 \times Post_t + \beta_3 \times New_p + \beta_4 \times Treat_z \times Post_t + \beta_5 \times Post_t \times New_p + \beta_6 \times Treat_z \times New_p + \beta_7 \times Treat_z \times Post_t \times New_p + \lambda_{z \times p} + \phi_{z \times t} + \varepsilon_{z,t,p}$$

Table 10 presents the key triple differences regression estimates where the response variable is the log of number of mortgage applications in Column (1), and log of number of mortgage loans in Column (2) in area z in year t for product-type p . The main explanatory variable is the interaction term of three indicator variables: $Treat_z$, $Post_t$, and New_p . $Treat_z$ is 1 if z is an area with a BancAlliance member bank, and 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 otherwise. New_p is 1 if p represents a new home purchase, and 0 if it represents refinancing. The sample here is from 2010 to 2019. I employ two fixed effects, namely the interaction of zip3 and product-type, i.e. $\lambda_{z \times p}$, and the interaction of state and year fixed effects, i.e. $\phi_{z \times t}$. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides evidence that new home purchase activity is more responsive to unsecured LendingClub loan activity in an area, relative to refinancing activity.

	(1)	(2)
	Log Mortgage Apps	Log Mortgage Loans
Treat X Post X New	0.0346*	0.0465**
	(0.0182)	(0.0194)
Zip3 X New FE	Yes	Yes
State X Year FE	Yes	Yes
Number of Observations	18,066	18,066
Adj R-squared	0.3845	0.4319
Number of Zip3s	905	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 11: Triple Differences: Impact on Mortgage Loans Across Income Bands

$$\begin{aligned}
Y_{z,t,b} = & \beta_{0,b} + \beta_{1,b} \times Treat_z + \beta_{2,b} \times Post_t + \beta_{3,b} \times IncBand_b + \beta_{4,b} \times Treat_z \times Post_t \\
& + \beta_{5,b} \times Post_t \times IncBand_b + \beta_{6,b} \times Treat_z \times IncBand_b \\
& + \beta_{7,b} \times Treat_z \times Post_t \times IncBand_b + \lambda_{z \times b} + \phi_{z \times t} + \varepsilon_{z,t,b}
\end{aligned}$$

Table 11 presents the key triple differences regression estimates where the response variable is the log of the number of all mortgage applications in Column (1), and the log of the number of all mortgages in Column (2), the log of the number of new home purchase mortgage applications in Column (3), and the log of the number of new home purchase mortgages in Column (4), the log of the number of refinancing mortgage applications in Column (5), and the log of the number of refinancing mortgages in Column (6), in area z in year t for income band b . The main explanatory variables in each analysis are the interaction term of three indicator variables: $Treat_z$, $Post_t$, and $IncBand_b$. $Treat_z$ is 1 if z is an area with a BancAlliance member bank, and 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 otherwise. $IncBand_b$ is 1 if the response variable in an area corresponds to income band b , and 0 if it represents a different income band. The benchmark income band here is $< \$40K$. The sample here is from 2010 to 2019. I employ two fixed effects, namely the interaction of zip3 and income band, i.e. $\lambda_{z \times b}$, and the interaction of state and year fixed effects, i.e. $\phi_{z \times t}$. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides evidence that middle income individuals are more responsive to unsecured LendingClub loan activity in an area, relative to others. Moreover, I do not see any effect for refinancing mortgage applications shown in Column (5).

	(1)	(2)	(3)	(4)	(5)	(6)
	All Apps	All Loans	New Apps	New Loans	Refi Apps	Refi Loans
Treat X Post X IB 40-60K	0.0231** (0.0102)	0.0581*** (0.0124)	0.0550*** (0.0163)	0.0622*** (0.0184)	0.0081 (0.0082)	0.0457*** (0.0108)
Treat X Post X IB 60-80K	0.0412*** (0.0126)	0.0790*** (0.0166)	0.0955*** (0.0210)	0.0979*** (0.0240)	0.0111 (0.0090)	0.0569*** (0.0114)
Treat X Post X IB 80-100K	0.0276** (0.0137)	0.0639*** (0.0180)	0.0888*** (0.0230)	0.0898*** (0.0260)	-0.0032 (0.0109)	0.0459*** (0.0136)
Treat X Post X IB 100-120K	0.0116 (0.0137)	0.0449** (0.0176)	0.0736*** (0.0235)	0.0738*** (0.0266)	-0.0171 (0.0124)	0.0278** (0.0137)
Treat X Post X IB >120K	0.0177 (0.0126)	0.0496*** (0.0171)	0.0824*** (0.0243)	0.0857*** (0.0277)	-0.0214* (0.0125)	0.0250* (0.0139)
Zip3 X IncBand FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	54,156	54,156	54,156	54,156	54,156	54,156
Number of Zip3s	905	905	905	905	905	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 12: Difference-in-Differences: Impact on All Mortgage Applications Across Income Bands

$$Y_{z,t,b} = \beta_0 + \beta_{1,b} \times Treat_z + \beta_{2,b} \times Post_t + \beta_{3,b} \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t,b}$$

Table 12 presents the difference-in-differences regression estimates for six subgroups, each corresponding to a different income band. The response variable is the log of number of mortgage applications in area z in year t for income band b . The main explanatory variable is the interaction of two indicator variables: $Treat_z$ and $Post_t$. $Treat_z$ is 1 if z is an area with a BancAlliance member bank, and 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 otherwise. The sample here is from 2010 to 2019. I employ two fixed effects, namely area fixed effects, i.e. γ_z , and the interaction of state and year fixed effects, i.e. $\phi_{z \times t}$. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides evidence that middle income mortgage applicants are more sensitive to unsecured LendingClub loan activity in an area, relative to other income bands.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	-0.0058 (0.0102)	0.0269* (0.0149)	0.0462*** (0.0156)	0.0416*** (0.0154)	0.0348** (0.0150)	0.0264** (0.0131)
Income Band (USD)	< 40K	40-60K	60-80K	80-100K	100-120K	> 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 13: Difference-in-Differences: Impact on All Mortgage Loans Across Income Bands

$$Y_{z,t,b} = \beta_0 + \beta_{1,b} \times Treat_z + \beta_{2,b} \times Post_t + \beta_{3,b} \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t,b}$$

Table 13 presents the difference-in-differences regression estimates for six subgroups, each corresponding to a different income band. The response variable is the log of number of mortgages in area z in year t for income band b . The main explanatory variable is the interaction term of two indicator variables: $Treat_z$ and $Post_t$. $Treat_z$ is 1 if z is an area with a BancAlliance member bank, and 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 otherwise. The sample here is from 2010 to 2019. I employ two fixed effects, namely area fixed effects, i.e. γ_z , and the interaction of state and year fixed effects, i.e. $\phi_{z \times t}$. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides evidence that middle income mortgage borrowers are more sensitive to unsecured LendingClub loan activity in an area, relative to other income bands.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	-0.0285** (0.0134)	0.0286* (0.0170)	0.0517*** (0.0170)	0.0463*** (0.0169)	0.0411** (0.0166)	0.0272** (0.0137)
Income Band (USD)	< 40K	40-60K	60-80K	80-100K	100-120K	> 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 14: Instrumented Difference-in-Differences: Impact On Mortgage Delinquencies

$$\begin{aligned}
1^{st} \text{ Stage: } \log(\text{No_Mortgages})_{z,t} &= \pi_0 + \pi_1 \times \text{Treat}_z + \pi_2 \times \text{Post}_t + \pi_3 \times \text{Treat}_z \times \text{Post}_t \\
&\quad + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t} \\
2^{nd} \text{ Stage: } \log(\text{No_Mortgage_Delinquencies})_{z,t,t+k} &= \beta_0 + \beta_1 \times \widehat{\log(\text{No_Mortgages})}_{z,t} + \gamma_z \\
&\quad + \phi_{z \times t} + \varepsilon_{z,t}; \quad k \in \{1, 2, 3\}
\end{aligned}$$

Table 14 presents the instrumented difference-in-differences (DDIV) regression estimates to study impact on mortgage delinquencies due to LendingClub loan activity in an area. I use mortgage data provided by Fannie Mae and Freddie Mac to conduct this analysis, which represents a subset of overall mortgage data, comprising about 40% of all mortgages. In the first stage, the response variable is the log of number of mortgage loans in area z at year t . The main explanatory variable here is the interaction of two indicator variables: Treat_z and Post_t . Treat_z is 1 if z is an area with a BancAlliance member bank, and 0 otherwise. Post_t is 1 if year t is 2015 or later, and 0 otherwise. Column (1) presents the coefficient of interest π_3 from this stage. In the second stage, the response variable is the log of number of mortgage delinquencies in area z from year t to $t+k$, where $k \in \{1, 2, 3\}$. The main explanatory variable here is the predicted values of log of number of mortgages, constructed using the coefficients from the first stage. Columns (2) - (4) present the coefficients of interest for number of delinquencies within 12 months, 24 months, and 36 months, respectively. The sample here is from 2010 to 2019. I employ two fixed effects, namely area fixed effects, i.e. γ_z , and the interaction of state and year fixed effects, i.e. $\phi_{z \times t}$. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides causal evidence that mortgage delinquencies do not increase disproportionately relative to the growth in mortgages when unsecured LendingClub loan activity leads to higher mortgage originations in an area.

	(1)	(2)	(3)	(4)
	Log No Mortgages	Delinq 12 mth	Delinq 24 mth	Delinq 36 mth
Treat X Post	0.0555*** (0.0182)			
Log No Mortgages		0.7328** (0.3478)	0.9916*** (0.3817)	1.0089*** (0.3695)
Zip3 FE	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes
Number of Observations	9,035	9,035	9,035	9,035
Number of Zip3	905	905	905	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Appendix

Figure 7: Growth In US Personal Loans And Contribution By FinTech Lenders

Figure 7 presents the growth of unsecured personal loans in the U.S. and the share of FinTech lenders. In each year, the overall length of the bar represents the total outstanding unsecured personal loan balance in billions of U.S. dollars. The portion of the bar highlighted in red represents the share of FinTech lenders, while the remaining portion represents loans originated by traditional lenders. This figure shows that over the past decade, most of the growth in this loan market has been driven by FinTech lenders. Data here has been collected from various reports provided by Transunion.

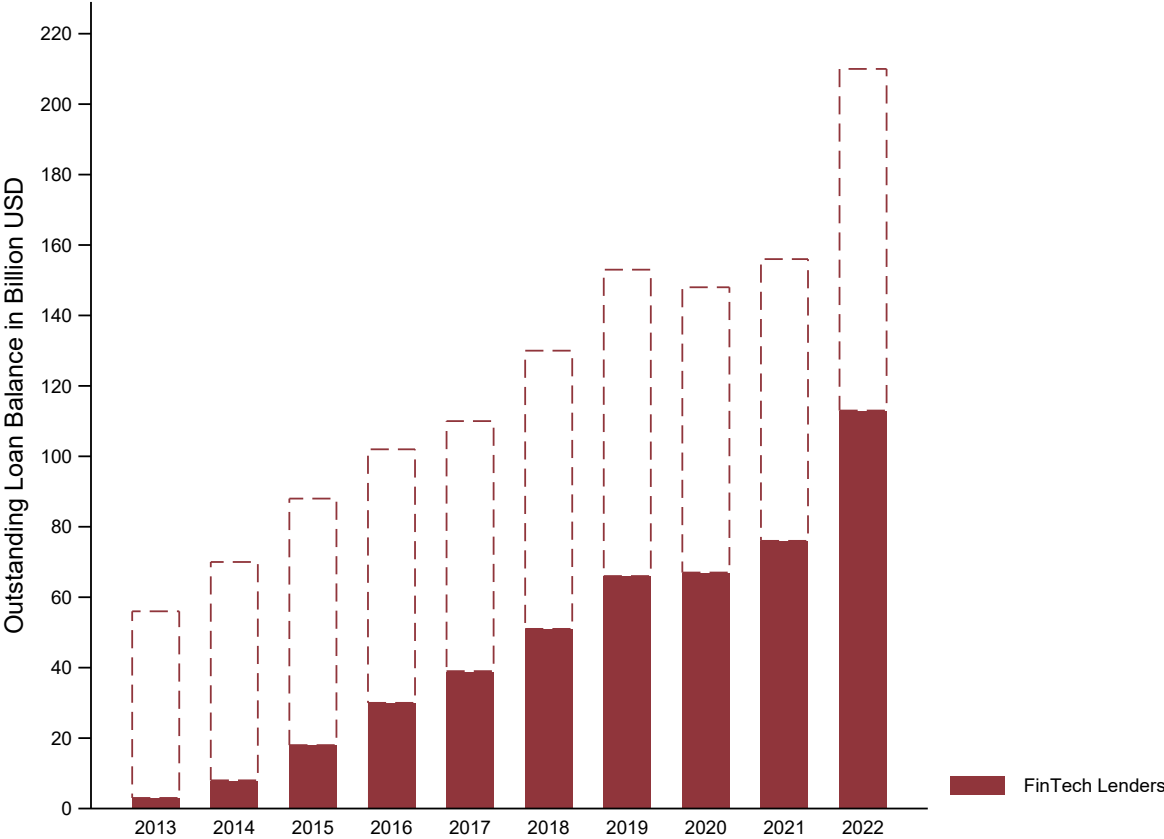


Figure 8: Geographic Variation in LendingClub Borrower Profile

Figure 8 presents the zip3 level variation in LendingClub borrower profile. The median values of these borrower characteristics in an area in a year are reported in Table 1.

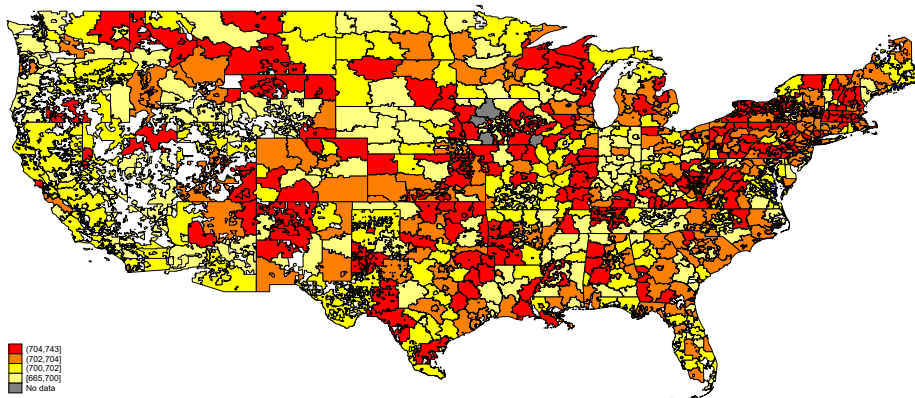
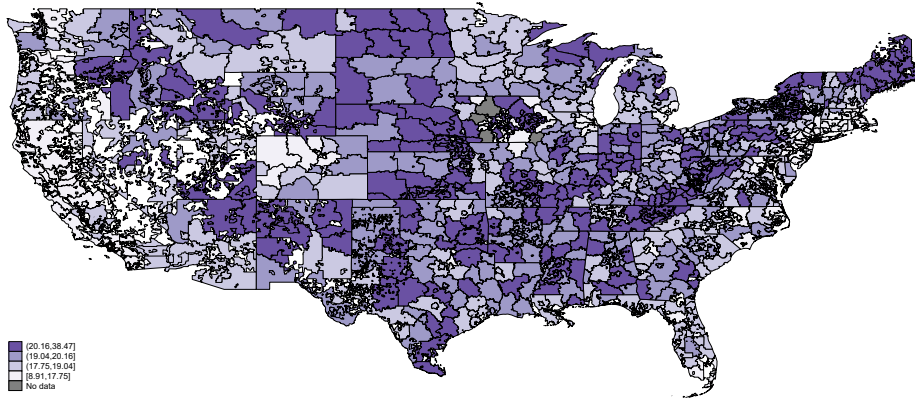
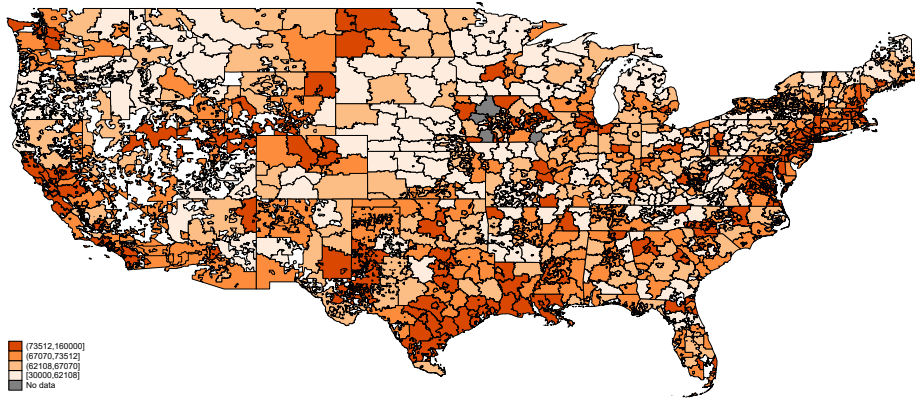
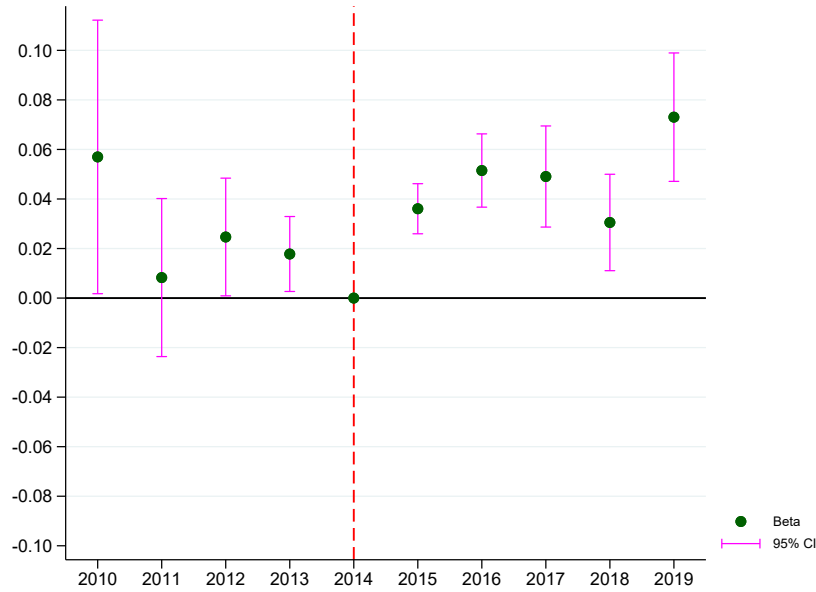


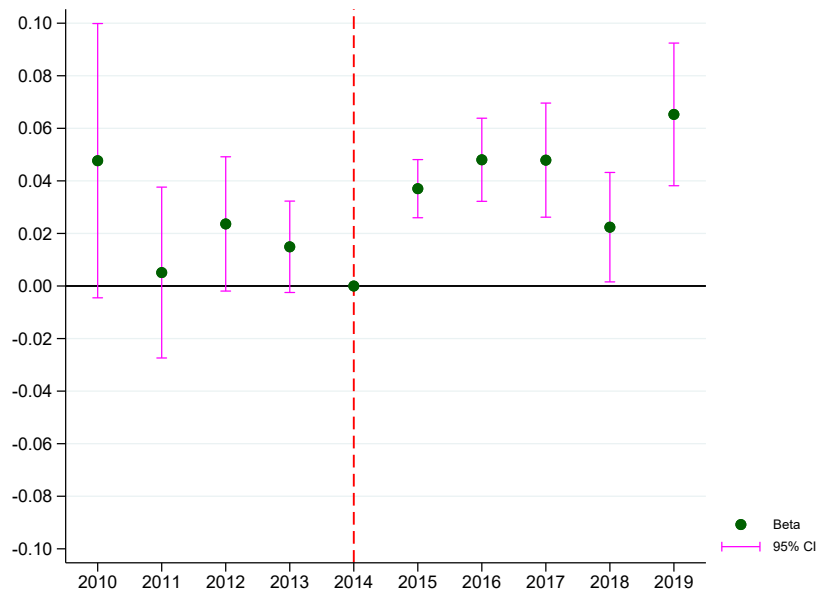
Figure 9: Robustness Test 1: Impact On Mortgage Activity

$$Y_{z,t} = \delta_0 + \sum_k \delta_{t-k} \times Treat_z \times Post_{t-k} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

Figure 9 plots the year-wise point estimates demonstrating the impact of LendingClub’s partnership with the BancAlliance network in 2015 on mortgage activity, when mortgage activity by FinTech mortgage lenders is excluded from the sample. I employ zip3, and the interaction of state and year fixed effects. All standard errors are clustered at zip3 level, which is the level of treatment. I show here that, even if we remove all applications and loans processed by FinTech mortgage lenders, mortgage activity was similar in treated areas versus control areas before 2015, and treated areas saw increased mortgage activity versus control areas after 2015.



(a) Year-wise Estimates of Mortgage Applications in Treated Versus Control Areas



(b) Year-wise Estimates of Mortgage Loans in Treated Versus Control Areas

Table 15: Difference-in-Differences: Impact on New Mortgage Applications Across Income Bands

$$Y_{z,t,b} = \beta_0 + \beta_{1,b} \times Treat_z + \beta_{2,b} \times Post_t + \beta_{3,b} \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t,b}$$

Table 15 presents the difference-in-differences regression estimates for six subgroups, each corresponding to a different income band. The response variable is the log of number of new home purchase mortgage applications in area z in year t for income band b . The main explanatory variable is the interaction term of two indicator variables: $Treat_z$ and $Post_t$. $Treat_z$ is 1 if z is an area with a BancAlliance member bank, and 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 otherwise. The sample here is from 2010 to 2019. I employ two fixed effects, namely area fixed effects, i.e. γ_z , and the interaction of state and year fixed effects, i.e. $\phi_{z \times t}$. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides causal evidence that middle income new home purchase applicants are more sensitive to unsecured LendingClub loan activity in an area, relative to other income bands.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	-0.0506*** (0.0175)	0.0148 (0.0217)	0.0464** (0.0204)	0.0435** (0.0191)	0.0406** (0.0178)	0.0320** (0.0142)
Income Band (USD)	< 40K	40-60K	60-80K	80-100K	100-120K	> 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 16: Difference-in-Differences: Impact on New Mortgage Loans Across Income Bands

$$Y_{z,t,b} = \beta_0 + \beta_{1,b} \times Treat_z + \beta_{2,b} \times Post_t + \beta_{3,b} \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t,b}$$

Table 16 presents the difference-in-differences regression estimates for six subgroups, each corresponding to a different income band. The response variable is the log of number of new home purchase mortgages in area z in year t for income band b . The main explanatory variable is the interaction term of two indicator variables: $Treat_z$ and $Post_t$. $Treat_z$ is 1 if z is an area with a BancAlliance member bank, and 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 otherwise. The sample here is from 2010 to 2019. I employ two fixed effects, namely area fixed effects, i.e. γ_z , and the interaction of state and year fixed effects, i.e. $\phi_{z \times t}$. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides causal evidence that middle income new home purchase borrowers are more sensitive to unsecured LendingClub loan activity in an area, relative to other income bands.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	-0.0535*** (0.0187)	0.0215 (0.0224)	0.0499** (0.0208)	0.0483** (0.0197)	0.0419** (0.0184)	0.0367** (0.0148)
Income Band (USD)	< 40K	40-60K	60-80K	80-100K	100-120K	> 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 17: Difference-in-Differences: Impact on Refi Mortgage Applications Across Income Bands

$$Y_{z,t,b} = \beta_0 + \beta_{1,b} \times Treat_z + \beta_{2,b} \times Post_t + \beta_{3,b} \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t,b}$$

Table 17 presents the difference-in-differences regression estimates for six subgroups, each corresponding to a different income band. The response variable is the log of number of refinancing applications in area z in year t for income band b . The main explanatory variable is the interaction term of two indicator variables: $Treat_z$ and $Post_t$. $Treat_z$ is 1 if z is an area with a BancAlliance member bank, and 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 otherwise. The sample here is from 2010 to 2019. I employ two fixed effects, namely area fixed effects, i.e. γ_z , and the interaction of state and year fixed effects, i.e. $\phi_{z \times t}$. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides causal evidence that middle income refinancing applicants are more sensitive to unsecured LendingClub loan activity in an area, relative to other income bands.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	0.0273** (0.0135)	0.0438*** (0.0163)	0.0498*** (0.0161)	0.0386** (0.0163)	0.0353** (0.0168)	0.0189 (0.0153)
Income Band (USD)	< 40K	40-60K	60-80K	80-100K	100-120K	> 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 18: Difference-in-Differences: Impact on Refi Mortgage Loans Across Income Bands

$$Y_{z,t,b} = \beta_0 + \beta_{1,b} \times Treat_z + \beta_{2,b} \times Post_t + \beta_{3,b} \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t,b}$$

Table 18 presents the difference-in-differences regression estimates for six subgroups, each corresponding to a different income band. The response variable is the log of number of refinancings in area z in year t for income band b . The main explanatory variable is the interaction term of two indicator variables: $Treat_z$ and $Post_t$. $Treat_z$ is 1 if z is an area with a BancAlliance member bank, and 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 otherwise. The sample here is from 2010 to 2019. I employ two fixed effects, namely area fixed effects, i.e. γ_z , and the interaction of state and year fixed effects, i.e. $\phi_{z \times t}$. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides causal evidence that middle income refinancing borrowers are more sensitive to unsecured LendingClub loan activity in an area, relative to other income bands.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	0.0034 (0.0164)	0.0427** (0.0189)	0.0538*** (0.0179)	0.0415** (0.0184)	0.0439** (0.0190)	0.0188 (0.0161)
Income Band (USD)	< 40K	40-60K	60-80K	80-100K	100-120K	> 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 19: Robustness Test 1: Baseline OLS - Impact On Mortgage Activity

$$Y_{z,t} = \beta_0 + \beta_1 \times \log(\text{No-LendingClub-Loans})_{z,t-k} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}; \quad k \in \{0, 1, 2\}$$

Table 19 presents the key regression estimates where the response variable is the log of number of mortgage applications in Columns (1), (2), and (3), and the log of number of mortgage loans in Columns (4), (5), and (6) in area z in year t . These variables are constructed after removing all mortgage applications and loans processed by FinTech mortgage lenders, using the list provided by Buchak et al. (2018). The main explanatory variables are the log of the number of LendingClub loans in area z in year $t - k$, where $k \in \{0, 1, 2\}$. The sample period is from 2010 to 2019. I employ zip3, and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. The table shows that LendingClub loan activity is positively correlated with overall mortgage activity in an area, even when mortgage activity generated by FinTech mortgage lenders is excluded.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Apps	Log Apps	Log Apps	Log Loans	Log Loans	Log Loans
Log LC Loans	0.0720*** (0.0100)			0.0725*** (0.0101)		
Log LC Loans.L1		0.0523*** (0.0065)			0.0492*** (0.0068)	
Log LC Loans.L2			0.0417*** (0.0055)			0.0411*** (0.0060)
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	7,223	7,223	7,223	7,223	7,223	7,223
Adj R-squared	0.0295	0.0265	0.0242	0.0251	0.0196	0.0197
Number of Zip3s	904	904	904	904	904	904

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 20: Robustness Test 1: Difference-in-Differences - Impact on Mortgage Activity

$$Y_{z,t} = \delta_0 + \delta_1 \times Treat_z + \delta_2 \times Post_t + \delta_3 \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

Table 20 presents the regression estimates where the response variable is the log of number of mortgage applications in Column (1) and log of number of mortgage loans in Column (2) in area z in year t . These variables are constructed after removing all mortgage applications and loans processed by FinTech mortgage lenders, using the list provided by Buchak et al. (2018). The explanatory variable is the interaction of dummy variables $Treat_z$ and $Post_t$. $Treat_z$ is 1 if area z is a treated area, i.e., it housed a member bank of the BancAlliance network in 2015, as shown in Figure 2. It is 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 if earlier. The sample period is from 2010 to 2019. I employ zip3 and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. This table shows that, even after excluding all mortgage applications processed by and loans originated by FinTech lenders in the mortgage market, mortgage activity increased significantly in treated areas after 2015 relative to control areas.

	(1)	(2)
	Log Mortgage Apps	Log Mortgages
Treat X Post	0.0265** (0.0124)	0.0259** (0.0128)
Zip3 FE	Yes	Yes
State X Year FE	Yes	Yes
Number of Observations	9,033	9,033
Number of Zip3s	905	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 21: Robustness Test 1: DDIV - Impact On Mortgage Applications

$$1^{st} \text{ Stage: } \log(\widehat{No_LendingClub_Loans})_{z,t} = \pi_0 + \pi_1 \times Treat_z + \pi_2 \times Post_t + \pi_3 \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

$$2^{nd} \text{ Stage: } \log(No_Mortgage_Apps)_{z,t+k} = \beta_0 + \beta_1 \times \widehat{log(No_LendingClub_Loans)}_{z,t} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}; \quad k \in \{0, 1, 2\}$$

Table 21 presents the results of the second stage of the instrumented difference-in-differences (DDIV) regression estimates. The response variable in this stage is the log of the number of mortgage applications in area z in year t . This variable is constructed after removing all mortgage applications and loans processed by FinTech mortgage lenders, using the list provided by Buchak et al. (2018). The main explanatory variable is the predicted values of the log of the number of LendingClub loans constructed using coefficients obtained in the first stage, as shown in Table 5. The sample period is from 2010 to 2019. I employ zip3 and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides causal evidence to show that, even after excluding all mortgage applications processed by and loans originated by FinTech lenders in the mortgage market, mortgage applications increased due to increase in the number of LendingClub loans in an area.

	(1)	(2)	(3)
	Log Apps.T	Log Apps.T+1	Log Apps.T+2
Log LC Loans	0.2685* (0.1398)	0.3456*** (0.1321)	0.2628** (0.1075)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	9,033	8,127	7,223
Number of Zip3s	905	904	904

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 22: Robustness Test 1: DDIV - Impact On Mortgage Loans

$$1^{st} \text{ Stage: } \log(\text{No_LendingClub_Loans})_{z,t} = \pi_0 + \pi_1 \times \text{Treat}_z + \pi_2 \times \text{Post}_t + \pi_3 \times \text{Treat}_z \times \text{Post}_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

$$2^{nd} \text{ Stage: } \log(\text{No_Mortgage_Loans})_{z,t+k} = \beta_0 + \beta_1 \times \log(\widehat{\text{No_LendingClub_Loans}})_{z,t} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}; \quad k \in \{0, 1, 2\}$$

Table 22 presents the results of the second stage of the instrumented difference-in-differences (DDIV) regression estimates. The response variable in this stage is the log of the number of mortgage loans in area z in year t . This variable is constructed after removing all mortgage applications and loans processed by FinTech mortgage lenders, using the list provided by Buchak et al. (2018). The main explanatory variable is the predicted values of the log of the number of LendingClub loans constructed using coefficients obtained in the first stage, as shown in Table 5. The sample period is from 2010 to 2019. I employ zip3 and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. This table provides causal evidence to show that, even after excluding all mortgage applications processed by and loans originated by FinTech lenders in the mortgage market, mortgage loan originations increased due to increase in the number of LendingClub loans in an area.

	(1) Log Loans.T	(2) Log Loans.T+1	(3) Log Loans.T+2
Log LC Loans	0.2621* (0.1426)	0.3019** (0.1326)	0.2119* (0.1124)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	9,033	8,127	7,223
Number of Zip3s	905	904	904

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 23: Robustness Test 2: Baseline OLS - Impact On Mortgage Activity

$$\log(\text{No_Mortgages})_{z,t} = \beta_0 + \beta_1 \times \log(\text{No_LendingClub_Loans})_{z,t-k} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}; \quad k \in \{0, 1, 2\}$$

Table 23 presents the key regression estimates where the response variable is the log of number of mortgage loans in area z in year t . This variable is constructed using conforming mortgage data provided by Fannie Mae and Freddie Mac, which represents a subset of overall mortgage data, comprising about 40% of all mortgages. The main explanatory variables are the log of the number of LendingClub loans in area z in year $t - k$, where $k \in \{0, 1, 2\}$. The sample period is from 2010 to 2019. I employ zip3, and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. As a result, using a different mortgage dataset, this table shows that LendingClub loan activity is positively correlated with mortgage activity in an area.

	(1)	(2)	(3)
Log LC Loans	0.0727*** (0.0235)		
Log LC Loans.L1		0.0253* (0.0146)	
Log LC Loans.L2			0.0154 (0.0100)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	7,225	7,225	7,225
Adj R-squared	0.0127	0.0025	0.0012
Number of Zip3s	904	904	904

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 24: Robustness Test 2: Difference-in-Differences - Impact on Mortgage Activity

$$\log(No_Mortgages)_{z,t} = \delta_0 + \delta_1 \times Treat_z + \delta_2 \times Post_t + \delta_3 \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

Table 24 presents the regression estimates where the response variable is the log of number of mortgage loans in area z in year t . This variable is constructed using conforming mortgage data provided by Fannie Mae and Freddie Mac, which represents a subset of overall mortgage data, comprising about 40% of all mortgages. The explanatory variable is the interaction of dummy variables $Treat_z$ and $Post_t$. $Treat_z$ is 1 if area z is a treated area, i.e., it housed a member bank of the BancAlliance network in 2015, as shown in Figure 2. It is 0 otherwise. $Post_t$ is 1 if year t is 2015 or later, and 0 if earlier. The sample period is from 2010 to 2019. I employ zip3 and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. As a result, using a different mortgage dataset, this table shows that mortgage loans increased significantly in treated areas after 2015 relative to control areas.

	(1) Log Mortgages
Treat X Post	0.0555*** (0.0182)
Zip3 FE	Yes
State X Year FE	Yes
Number of Observations	9,035
Number of Zip3s	905

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 25: Robustness Test 2: DDIV - Impact On Mortgage Applications

$$1^{st} \text{ Stage: } \log(\widehat{No_LendingClub_Loans})_{z,t} = \pi_0 + \pi_1 \times Treat_z + \pi_2 \times Post_t + \pi_3 \times Treat_z \times Post_t + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

$$2^{nd} \text{ Stage: } \log(No_Mortgages)_{z,t+k} = \beta_0 + \beta_1 \times \widehat{\log(No_LendingClub_Loans)}_{z,t} + \gamma_z + \phi_{z \times t} + \varepsilon_{z,t}$$

$$k \in \{0, 1, 2\}$$

Table 25 presents the results of the second stage of the instrumented difference-in-differences (DDIV) regression estimates. The response variable in this stage is the log of the number of mortgage loans in area z in year t . This variable is constructed using conforming mortgage data provided by Fannie Mae and Freddie Mac, which represents a subset of overall mortgage data, comprising about 40% of all mortgages. The main explanatory variable is the predicted values of the log of the number of LendingClub loans constructed using coefficients obtained in the first stage, as shown in Table 5. The sample period is from 2010 to 2019. I employ zip3 and the interaction of state and year fixed effects using γ_z and $\phi_{z \times t}$, respectively. All standard errors are clustered at zip3 level, which is the level of treatment. As a result, using a different mortgage dataset, this table provides causal evidence that mortgage loan originations increased due to increase in the number of LendingClub loans in an area.

	(1)	(2)	(3)
	Log Mortgages.T	Log Mortgages.T+1	Log Mortgages.T+2
Log LC Loans	0.5489** (0.2343)	0.5619** (0.2393)	0.3724* (0.2062)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	9,035	8,129	7,225
Number of Zip3s	905	904	904

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$