'I'll Have What She's Having':
Identifying Social Influence in Household Mortgage Decisions*

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We find evidence that neighbors apply an important economic force on households' mortgage choices. We use household mortgage data, geolocated real estate data, and a recently developed research design to identify the existence of social influence effects in three important household mortgage choices. We estimate the effects of peer activity on the census block while controlling for peer activity at slightly larger geographies to identify the existence of social influence effects in several important household mortgage choices. Households are 1.4% to 3.5% more likely to choose a particular lender, 1.5% more likely to choose an adjustable rate mortgage (ARM), and 9.8% more likely to refinance if the share of their block-neighbors with that lender, with an ARM, or who have recently refinanced increases by ten percentage points, respectively. To provide further evidence for our hypothesis, we apply our research design to two groups: households moving to new neighborhoods and households that are not owner-occupied. We find that movers are not initially affected by their hyperlocal peers and second property owners never are. Finally, we complement these empirical strategies in the lab by experimentally assigning peers and peer decisions in a variety of ways. We conclude that hyperlocal peers have an economically significant impact on how households make their own mortgage decisions.

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1 Introduction

Mortgage decisions are important household financial decisions. Most homebuyers are unable to buy homes outright creating a need for mortgages and the financial intermediaries that offer them. Across the United States, nearly 50 million owner occupied, mortgaged households[2] owe a combined $10 trillion in mortgage debt.[3] With thousands of lenders[4] offering fixed rate mortgages (FRMs) and adjustable rate mortgages (ARMs), households must decide what type of loan to apply for and where. And after making it through the loan origination process, households must everyday incorporate new information and choose whether or not to refinance. Poor lender choice can cost borrowers their livelihoods and neighborhoods their stability (Engel and McCoy, 2007; Agarwal et al., 2014). Keys, Pope, and Pope (2014) found that a fifth of households for whom refinancing was profitable failed to do so and cost themselves more than $10,000 each. In order to effectively design policies that improve household decision making and implement regulations that better align the incentives of financial intermediaries and households, economists and policymakers must first understand the household decision making process. How do households make complex mortgage decisions? In this paper, we present evidence of a social influence effect that operates at very local levels.

Theory suggests that households making mortgage decisions consider the pricing and terms of the available mortgage options and their private personal characteristics (Agarwal, Driscoll, and Laibson (2013); Campbell and Cocco (2003); Coulibaly and Li (2009)). Results from a 2015 Consumer Financial Protection Bureau (CFPB) survey of two thousand borrowers who purchased homes in 2013 suggest otherwise. Almost half of consumers considered only a single lender and two thirds cited friends, relatives, and co-workers as important sources of information (CFPB, 2015). Our paper rigorously identifies the revealed importance of these social influence effects using archival data and confirms a causal relationship using laboratory

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[2] Accessed September 21, 2016:
http://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk.

[3] Accessed September 21, 2016: https://www.federalreserve.gov/econresdata/releases/mortoutstand/current.htm

[4] Between 1990 and 2014, the Home Mortgage Disclosure Act data reports 23,406 unique mortgage lenders operating in the United States.

experiments. To our knowledge, ours is the first paper documenting the economic importance of neighbor influence on household mortgage decisions.

Households' peers are not randomly assigned, so the challenges to identifying social influence are severe. Casual observation might mistake endogenous group formation or correlated unobservables for social influence. To overcome these problems, we use a comprehensive dataset of mortgage loans and a recently developed identification strategy that leverages our precisely geolocated data. Our final dataset includes information on the lender, the borrower, the property securing the loan, and the loan itself for all mortgage loans originated in Los Angeles between 1990 and 2012. Importantly, we know the precise latitude and longitude of the property for each mortgage. This level of detail allows us to use a powerful research design that identifies social influence by estimating the effects of hyperlocal neighbors' mortgage decisions (those on the household's residential block) while controlling for the same decisions at a slightly larger geography (residential block plus adjacent blocks).[5] We further leverage our detailed dataset by using movers and second property homeowners to rule out a variety of lingering endogeneity concerns.

Los Angeles census blocks correspond closely to city blocks and are inhabited by an average of 25 households. Figure 1 presents an example of our identification strategy. Is a household more likely to refinance if more households on its block have recently refinanced controlling for the number of households in its neighborhood (block plus adjacent blocks) that have recently refinanced? The key assumption is that, while households can choose in which neighborhood to live, they are less likely to choose, or be able to choose, a specific block. If true, then conditional on its neighborhood peers, a household's block peers are quasi-randomly assigned. Throughout this paper we will refer to the two areas of interest as blocks (census blocks) and neighborhoods (census block *and* the census blocks adjacent to it). Also, we call the two peer groups block peers (households that live on the same census block) and neighborhood peers (households that live in the same neighborhood). Our strategy uses within-neighborhood variation in activity to identify a block peer effect.

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[5] See Bayer, Ross, and Topa (2008) for the introduction of this method to the literature and Bayer, Mangum, and Roberts (2016) for an example of this strategy being used in real estate decisions in Los Angeles.

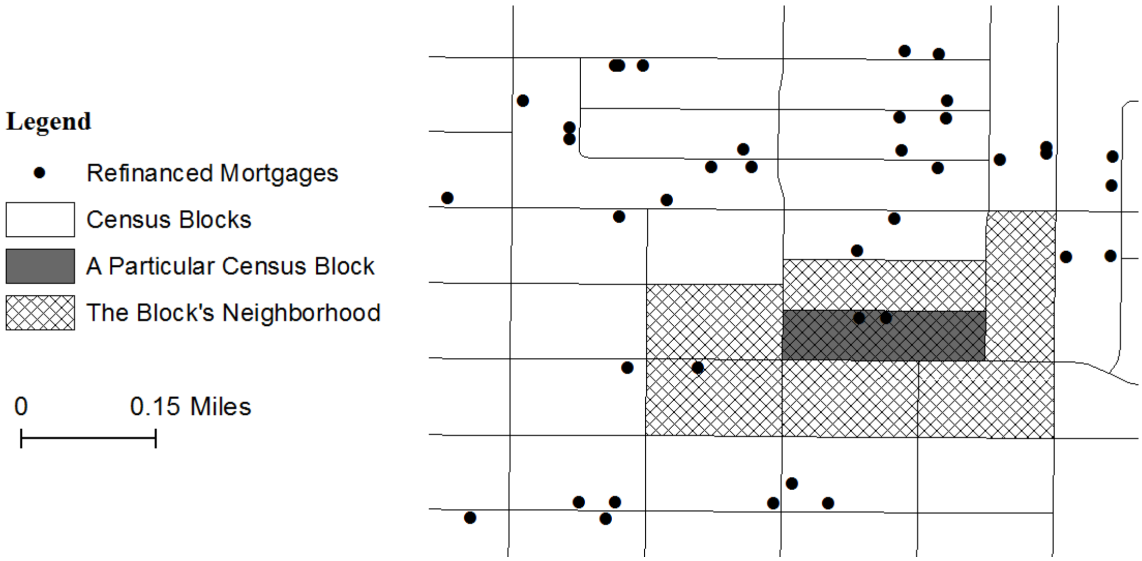

Figure 1: Nearby Mortgages Refinanced in the Previous Six Months. Census blocks follow city blocks and are inhabited by an average of twenty-five households. Our identification strategy asks if a household's probability of refinancing increases as the number of households on its block (shaded region) that have recently refinanced increases controlling for the number of households in its neighborhood (hatched region; note this include the block itself) that have recently refinanced.

Reassuringly, we find that households behave very similarly to their neighborhood peers (those households that live either on the same census block or on an adjacent one). But this result by itself cannot confirm the existence of a social influence effect. The non-random reasons households originally choose their neighborhoods, the many correlated characteristics of households in the same neighborhood, and their shared exposure to shocks all cause correlations between households' mortgage decisions and the decisions of their neighborhood peers. However, even after controlling for the neighborhood effect, we find that households behave especially like their very local, block peers. In other words, the identification strategy identifies block peer effects happening over and above any neighborhood effects. We take this is as evidence for the existence of a hyperlocal social influence effect.

The richness of our dataset allows us to control explicitly for a variety of characteristics of the property, the loan, and the borrower. And the size of our dataset allows us to include a variety of fixed effects notably, in some specifications, a lender fixed effect. Our key result, that block peers matter over and above neighborhood peers, is robust across model specifications and mortgage decisions. Alternative explanations – lender effects, household preference updating, or macroeconomic effects – cannot convincingly explain all of our results. We conclude that the social influence of block peers plays an important role when households decide from which lender to borrow, whether to choose an adjustable or fixed interest rate, and if and when to refinance. Specifically, households are 1.4% to 3.5% more likely to choose a particular lender, 1.5% more likely to choose an adjustable rate mortgage (ARM), and 9.8% more likely to refinance if the share of their block-neighbors with that lender, with an ARM, or who have recently refinanced increases by ten percentage points, respectively. In short, hyperlocal social influence effects matter in household mortgage decisions.

To paint a more complete picture and to rule out lingering endogeneity concerns, we apply our identification strategy to two subsamples: households moving to new neighborhoods from more than ten miles away and households that own second properties they do not occupy. Consistent with our key finding, we find that the lender choice and ARM decision of households moving to a new area are not affected by the decisions of their new block peers. Similarly, we find that when a mortgage secured by a non-owner-occupied property is refinanced, its choice of ARM or FRM is unaffected by the decisions of the households around it.[6] Next, we create all pair matches of households living in the same neighborhood and confirm the lender choice effects by documenting that households living on the same block are more likely to use the same lending institution. Finally, we use a matching strategy that matches outstanding loans in different census tracts (similar in size to zip codes) but which share a number of characteristics. We find that household refinance decisions are influenced by their block peers, but not the block peers of their match.

We remain agnostic as to potential transmission mechanisms. Households may be influenced by their neighbors for at least three reasons. First, they may learn from their neighbors – a household may not have been aware that an adjustable rate mortgage makes sense for them or that refinancing could save them money. We call this effect social learning. The second potential

[6] In unreported results, we find that (1) for the group of households we see purchase a home in a new neighborhood and then refinance as occupants that their initial ARM choice is unaffected by any hyperlocal social influence but that their ARM choice when they refinance is; and (2) that non-occupant owners behave especially like the block peers around the properties where they *do* currently live. We are in the process of confirming the robustness of these results.

mechanism, social utility, exists when a household's utility is increased if they make the same decision as a peer. For example, a household might choose a fixed rate mortgage if their peers do, because their peers can then help them refinance optimally. Finally, households might suboptimally herd with their neighbors. Also called information cascades, this phenomenon occurs when a household ignores its own private information and instead follows the crowd. The goal of this paper is to identify that social influence effects matter in household mortgage decisions and that the magnitudes of these effects are important. We leave uncovering the precise mechanism(s) driving these effects to future work.

Our paper adds to a small literature examining the role of peers and social influence in household real estate decisions. Bailey, Cao, Kuchler, and Stroebel (2016) find that social influence from friends has important consequences on real estate purchasing decisions. Bayer, Mangum, and Roberts (2016) and Gupta (2016) find that nearby households play a role in the decisions to purchase and default, respectively. The paper closest to ours, Maturana and Nickerson (2016), uses a sample of teachers in Texas. They find that teachers who are randomly assigned the same off-period influence each other's refinancing decisions. Our paper contributes to the literature a careful study using a universal sample of homeowners which explores multiple household mortgage decisions and concludes that social influence effects in household mortgage decisions are ubiquitous and economically important. Each of these papers, ours included, uses just a piece of the households' social network pie and therefore produces conservative estimates of the true social influence effect. Future work will need to find ways of simultaneously considering the influence of co-workers, family, and friends to uncover the magnitude of the entire social influence effect.

Our paper also adds to a large body of empirical work documenting the importance of a variety of factors for explaining household mortgage decisions. Demyanyk and Loutskina (2015), Fuster and Vickery (2014), and Di Maggio, Kermani, Korgaonkar (2015) provide evidence for the importance of government regulation and deregulation in mortgage decisions. Another line of research has concluded that lending standards affect household mortgage decisions (Agarwal, Amromin, Ben-David, Evanoff, 2015; Dell'Arriccia, Igan, Laeven, 2012; Mian and Sufi, 2009). Moreover, competition in the lender market can also play an important role (Amromin and Kearns, 2014; Scharfstein and Sundaram, 2014). Finally, other work has focused on individuals, finding that households' decisions are influenced by their expectations (Adelino, Schoar, and Severino (2016)), lack of education and understanding (Agarwal, Ben-David, and Yao (2014); Keys, Pope, and Pope (2014)), and strategic considerations (Mayer, Morrison, Piskorski, and Gupta (2014)).

We organize the rest of the paper as follows. Section II describes the identification strategies we use and explains the strengths and limitations of each approach. In section III we describe the data sources and sample construction. Our key results supporting the hypothesis that social influence matters are presented in section IV. Section V concludes with policy implications and directions for future work. Appendices include definitions of important variables and the results of robustness tests.

2 Our Strategies for Identifying Social Influence

Identifying social influence effects is difficult. Households in similar stages of life, with similar incomes, using the same institutions, and facing the same market conditions will make similar decisions. And since households choose where to live based, in large part, on the people who will be living near them and the characteristics of the neighborhood there will necessarily be correlations between the mortgage decisions made by households and the decisions made by their neighbors. In short, there are two problems. First, similar households choose to live together and similar households make similar mortgage decisions (endogenous group formation). Second, households living in the same neighborhood share all the characteristics of that neighborhood, some of which will remain unobserved to the econometrician (correlated unobservables). A random assignment of peer groups fixes this problem.

Our baseline strategy utilizes the detailed geographic information we have on the mortgaged property. Using the latitude and longitude of the property we are able to map every mortgage transaction to its census block. We combine this level of geographic detail with the assumption that households can choose which neighborhood (block plus adjacent blocks) to live in but not which specific block. This assumption means that, conditional on neighborhood, block peers are randomly assigned and consequently that endogenous group formation and correlated unobservables no longer bias estimations.[7] There are at least two reasons to assume the assumption is valid. First, households might be indifferent between households located on adjacent blocks. Second, household availability constraints mean that buyers might not have the option to live on a specific block in their desired neighborhood.

Consider the following example. The Joneses choose to move to a new neighborhood in Los Angeles. They are interested in living somewhere in the northern part of the city shown in Figure 2.

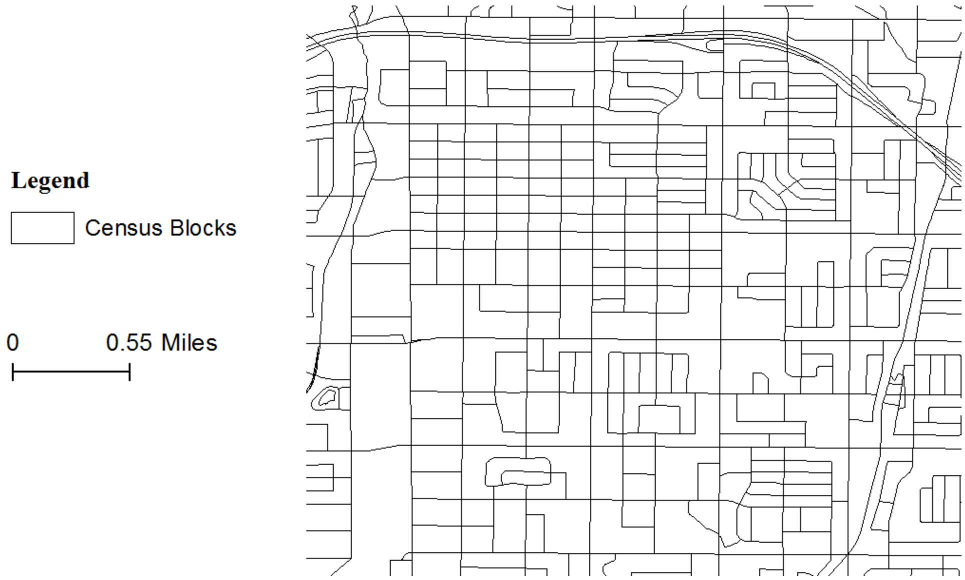

Figure 2: Census block delineations in Los Angeles. This figure presents census blocks in a northern part of Los Angeles. For more information on how census blocks are constructed see https://www2.census.gov/geo/pdfs/reference/GARM/Ch11GARM.pdf.

They spend an afternoon driving around, looking at houses, and becoming acquainted with the various small neighborhoods. In the end, they decide to try and find a property in the neighborhood shown in Figure 3. The neighborhood is located a convenient eight blocks south of the freeway and has two parks within walking distance.

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[7] It is this conditional-on-neighborhood-then-as-if-random observation that Bayer, Ross, and Topa (2008) made which enabled their design of this powerful identification strategy.

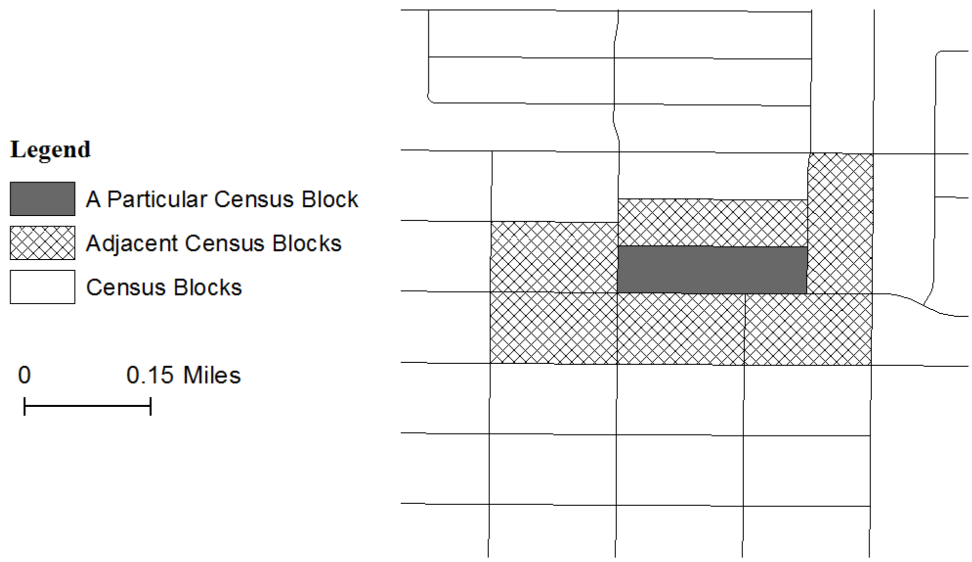

Figure 3: Adjacent Polygon Neighborhood Example. This figure presents a census block and the adjacent census blocks. Combined, these make up a neighborhood. The average neighborhood in Los Angeles is made up of *xx* blocks.

The example of the Jones family is clearly contrived. We use it to illustrate the plausibility of our assumption that households choose neighborhoods first and then specific houses within a neighborhood. In the event that households choose larger areas of interest first and then begin looking for specific households our assumption is especially met. There are certainly examples of this sort of behavior. A household accepts a job at Purdue University and then decides to live anywhere West Lafayette, not just a specific one block radius area, and then searches the entire town for a house. In this case, both block peers and neighborhood peers will be randomly assigned. We therefore view our working definition of neighborhood (block plus only adjacent blocks) as the location that households are nonrandomly choosing as very conservative.

There are no perfect assumption validity tests, but we use the available data to try and confirm that our assumption is reasonable. In table 3, we look at every house purchased with a mortgage between 2008Q1 – 2011Q4, and then compute the absolute value of the difference between the purchase loan / purchased property and the average of other houses on the block. Next, we compute the same difference but between the purchase loan and the average of houses in the adjacent blocks (*not* including the block itself, so that the two groups, block peers and adjacent block peers, are mutually exclusive.). These absolute values are averaged over all purchase loans and presented in columns 1 and 2. The third column presents the difference between these two values. A negative value means the house is less different from its block than its neighborhood. The fourth column tests whether this difference in differences is statistically different from zero. The difference in differences are not economically meaningful. I.e., households are no more different from their neighborhood peers than their block peers. This evidence supports the assumption that a household, conditional on choosing a certain neighborhood, is randomly assigned a block and thus randomly assigned a block peer group.

Our baseline strategy is written by the following linear probability model,

$$y_{it} = \alpha + \beta_1 * blockshare_i + \beta_2 * neighborhoodshare_i + \delta * \boldsymbol{X_i} + \tau_t + \varepsilon_{it} \qquad (1)$$

where y_{it} is the mortgage decision, always a binary outcome, made by household *i* at time *t*. Our parameter of interest is β_1 which is defined as the share of households on the block that have made the given decision (e.g., choose an ARM, refinance). The key control variable is *neighborhoodshare* which is defined as the share of households in the neighborhood that have made a given decision. Since the block peer decisions are included in the *neighborhoodshare* variable, the parameter β_1 picks up the outsized effect of block peers. We consider a positive β_1 as evidence of hyper local social influence effects. We vary the controls across specifications. But often included are borrower and borrower-loan controls, denoted $\boldsymbol{X_i}$, and time fixed effects, denoted γ_t. We also include geographic-level fixed effects which will be discussed in detail in the results section. We use Stata and the user create command *reghdfe* for estimation (Correia, 2016).

The bulk of our analysis uses equation (1) on the sample of refinance loans to present our key results. We use refinance loans and not purchase loans because refinance loans are made by households who have lived on the census block and are thus at risk for social influence from their block peers. Purchase loans will prove useful in placebo and falsification tests, in ways further described below. If our assumption is valid, there is no more work to be done. I.e., block peers are perfectly randomly assigned and our models therefore estimate a peer effect. But since we cannot be certain of the complete validity of our assumption we use two subsamples, namely, households moving to new neighborhoods and households that own but do not occupy second homes, to rule out some remaining endogeneity concerns. Analysis of each subsample can provide evidence consistent with our hypothesis – that there exists a social influence effect operating over short distances.

Movers allow our research design to test two specific predictions consistent with our overall hypothesis. The first is that movers, when making purchase loans, do not behave like their new neighbors. Movers have not yet had meaningful interactions with their new block peers, and so have yet to be socially influenced by them. We expect that the neighborhood effects, estimated by β_2, will be significant because of endogenous group formation and correlated unobservables, but not necessarily social interaction. On the other hand, β_1, which estimates only a hyperlocal social influence effect will not be relevant for movers. The second prediction is that households that move will behave like the block peers they left behind.[8] They have had social interactions with this group of peers and will continue to make decisions inspired by these interactions. This test is particularly compelling because many of the old neighborhood-level effects, like the availability of local mortgage lenders, will now be much less relevant.

Households wealthy enough to purchase second homes, for any combination of investment and consumption, are different than the average American household. But they provide a useful group for testing for local social influence effects. Specifically, if households own second homes but do not occupy those houses, then their mortgage decisions should be unaffected by a local social influence effect. We can further test whether or not the mortgages secured by their primary residences are affected by social influence.[9] Findings from these analyses provide strong support for the existence of a social influence effect, not only because they are consistent with this effect, but because there are few convincing alternative hypotheses that can explain this result.

Our baseline model, model (1), requires that the outcome variable be a binary outcome, e.g., refinance or not, borrow from Wells Fargo or a different lender. This requires us to abstract

[8] We are still verifying the robustness of this result.
[9] Another analysis we are confirming robustness on before reporting.

away from much of the richness of our data. We know the exact lender of each loan, and there are more than one thousand unique lenders in Los Angeles, but we are unable to incorporate this richness into our baseline model. We solve this problem by slightly adjusting the dataset construction and the model specification. Specifically, we take all outstanding refinance loans in Los Angeles as of 2011Q1 (purchase loan lender decisions are not subject to social influence since households have not been living on the block when the decision is made) and construct every possible pair of loans where both households are in the same neighborhood. We then tag those that are in the same census block, and those that share the same lender. Finally, we follow Bayer, Ross, and Topa (2008) and estimate the following equation:

$$L_{ij} = \rho_g + \alpha_0 R_{ij} + \varepsilon_{ij}, \tag{2}$$

where *i* and *j* are two households that live in the same neighborhood, L_{ij} is a dummy equal to 1 if the households share a lender, ρ_g is a geography fixed effect, and R_{ij} is a dummy equal to 1 if the households reside in the same block.

The final empirical design requiring its own introduction combines model (1) with an outstanding loan matching methodology. We match households living in different parts of Los Angeles but sharing demographic characteristics and observable attributes on their outstanding loans. And then estimate the effect of the first household's peers' decisions and his matches' peers' decisions on his own decision using the following model,

$$\begin{aligned} y_{ij} = \alpha + \beta_1 * blockshare_i + \beta_2 * neighborhoodshare_i + \gamma_1 \\ * blockshare_j + \gamma_2 * neighborhoodshare_j + \varepsilon_{ij} \end{aligned} \tag{3}$$

where *i* and *j* are two households that live in different census tracts, but whose loans share a common lender, purpose (refinance or purchase), interest rate type (adjustable or fixed), and quarter when the outstanding loan was originated. Further, households *i* and *j* both either have co-applicants on the loan or not, are in the same income quartile, and have primary borrowers that are both the same race. In the event that there are multiple qualifying matches, ties are broken based on the dollar amount of the outstanding loan and the incomes of the two households.

Our empirical strategy can be summarized as follows. Households do not randomly choose where they live and therefore do not randomly choose their peers. However, conditional on narrowly defined neighborhoods, the specific block households live on look as if randomly assigned. This allows us to use a strategy that estimates peer effects by modelling household mortgage decisions as a function of their block peers' decisions while controlling for their neighborhood peers' decisions. We use households moving to new neighborhoods and properties owned by non-occupants as compelling falsification and placebo tests. However, there always remain lingering endogeneity concerns that the best empirical identification strategies cannot fully handle.

We use a variety of laboratory experiments to reduce these concerns. Specifically, it is possible that our identified social influence effects could be due in part to unobservable correlations or sorting within neighborhoods. Experimentally manipulating peers serves to causally test our hypothesis in a way that would prove exceptionally challenging using conventional econometric techniques. In order to test our effect, we ran a pilot experiment using sixty people, randomly varying their existing peer group as well as, at least in some cases, their new peer group.

Participants were assigned one of two rooms of individuals. In all cases, participants were brought into a room of between 5-7 people and were told that they would be involved in a choice task where they would be asked to choose which mortgage option that they would prefer (FRM versus ARM) based on current mortgage rates and risks. They were told to read information regarding these two mortgage options and choose the option they wanted (FRM versus ARM). Participant's choices would then be recorded and the proportion of those choosing each option would be revealed at the end of each choice trial to all individuals in the room (i.e., one's peers). However, these proportions were randomly varied as a function of the experiment. In one room, it was revealed that between 72.4-84.8% chose a FRM; in the other room, it was revealed that this same majority percentage chose an ARM. After making their first decision, individuals were told that they would be making the ARM versus FRM mortgage decision in nine future periods/trials, being informed after each trial about the majority choosing a FRM (ARM).

In addition to exogenously varying information regarding what their nearby peers in their particular room have chosen, we also sought to replicate our moving result. We did this by splitting participants into one of three 'moving' treatment groups and then varying a) whether they switched rooms during their mortgage choice selection and b) at what point they switched rooms. Therefore, our three moving treatment groups were as follows: Participants either stayed in the same room for all ten sessions, switched rooms after two trials (i.e., they were exposed to one peer group and then moved to a different room with a new peer group that they spent a majority of their decision time with), or they switched after eight trials (i.e., they spent a majority of their time with the first peer group and moved later on to a new peer group). Our hypothesis was that participants who stay in the same place will conform to their peers the most. Participants who switch early (after trial two) should be more likely to conform to their new room (i.e., look like their new peers--replicating our earlier refinancing result). Participants that switch rooms much later are the least likely to conform with their new peers.

3 Data

3.1 Data Sources & Description

Our database of mortgage transactions is compiled by CoreLogic, which acquires data from mortgage deeds published by local tax assessor's office. CoreLogic is a mortgage level dataset and reports, for each loan, the names of the buyers and sellers, the date of the transfer, the type of transaction (purchase loan or refinance), the loan value, whether the interest rate on the loan is fixed or adjustable, the lender, and the latitude and longitude of the property. We use the latitude and the longitude to determine the census block of the property securing the mortgage. Census blocks are roughly similar to city blocks and are populated by an average of twenty-five households. Census block groups are the next smallest geography defined by the Census and are made up of approximately ten census blocks.

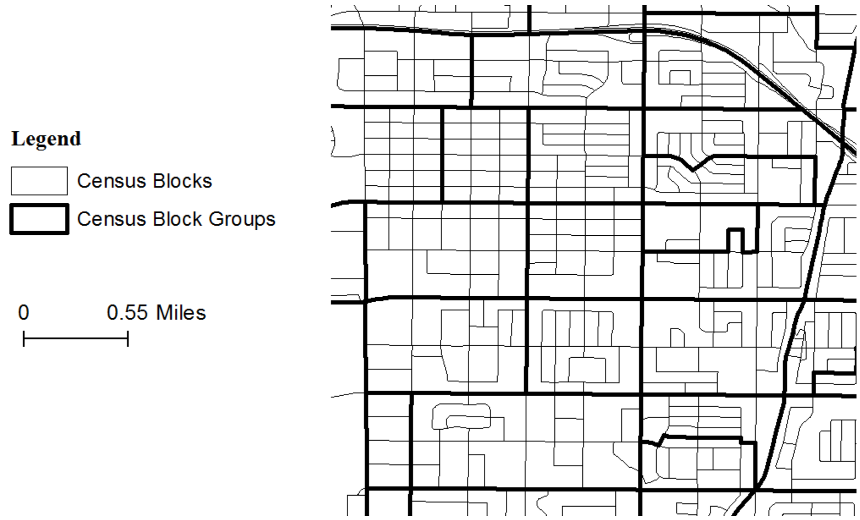

Figure 4: Census block group delineations in Los Angeles. This figure presents census blocks in a northern part of Los Angeles. Outline in a thick, black border are census block groups, the second smallest geographic delineation used by the Census.

While we use census block group fixed effects as important controls in some specifications, we choose to use the block plus adjacent blocks as our measure of neighborhood for two key reasons. First, using adjacent block neighborhoods removes the artificial census block group border. That is, we want to define a block that is adjacent to another block in a different census group as being in the block's neighborhood. Second, it's a more conservative definition. It might be the case that a household, when picking where to live, does prefer one part of the census block group to another, weakening our assumption. By defining a neighborhood as just a block and the adjacent blocks we make a stronger case for our assumption. The benefit of using census block groups as the larger area definition is that including census block group fixed effects becomes exceptionally powerful. For this reason, we replicate all of our tests using this measure of neighborhood. These results can be found in the appendix.

We chose Los Angeles as the focus sample of study for three reasons. First, Los Angeles is the second-largest city in the United States, and has a diverse ethnic and racial population. Second, Los Angeles is an important world economic center. And third, on a pragmatic level, Los Angeles was the largest city with long panel data and reliable non-missing variables.

The Home Mortgage Disclosure Act (HMDA) data is a separate mortgage level database that lists all mortgage applications made to qualifying lending institutions. This dataset includes information about the loan, including its purpose (purchase or refinance), dollar amount, the census tract of the underlying property, the year of the application, and whether or not it was approved. The dataset also details information on the applicants, specifically their race, sex, and income. HMDA uses a specific lender identification number to mark distinct lending institutions. This identification number is matched to the lender's name in the HMDA Lender File compiled by Dr. Robert Avery.

We merge together these three datasets – the two mortgage level datasets and the bridge file – to create a rich, detailed dataset of all the mortgage transactions that take place in Los Angeles County. We focus our attention on the time period between 2008 and 2011. We view the "bubble period" of 2002 – 2006 marked by very high levels of real estate value growth as too anomalous a setting to confidently identify the importance and ubiquity of social influence in household mortgage decisions. We believe that future work should separately try to understand how the bubble and social influence were shaped by each other.

3.2 The Samples

The goal of our study is to identify social influence in *household* mortgage decisions. We are consequently interested only in the decisions made by household borrowers as opposed to institutions or real estate investors. We consequently drop properties owned or being purchased by institutions (trusts, banks, business, and government and nonprofit organizations). We also drop properties that are simultaneously held by the same owner with more than one other property assuming that if the owner of a property owns more than two properties at one time she is not what we are thinking of when we say household.[10] We also drop purchase mortgages where the house involved sells for less than $1 or the transaction is tagged as one not at arms-length. Observations that are missing key variables – lender code, date, location – are also dropped. The final sample is summarized in table 1.

[10]This group of real estate buyers is interesting in its own right and the focus of work by Bayer, Mangum, and Roberts (2015), but is outside the scope of the current project.

Approximately 80% of the loans in our sample are refinance loans and 20% have adjustable interest rates.[11] The average loan amount is approximately $330,000, which, for purchase loans, translates to an average loan to value (LTV) of about 70%. Reassuringly, the median LTV is 80%, the cutoff above which many lenders require the borrower to purchase mortgage insurance. Activity is slower in 2008 and 2009 but roughly consistent during the entire time period. In Panel B of Table 1, we see that about half of all mortgage loans are made by banks and a quarter by mortgage companies. The lender with the highest number of loans in our sample is Wells Fargo. Note that they account for just 13% of lending activity. Our sample contains more than 2500 distinct lending institutions.

In Panel C of Table 1 we present information on characteristics of the households. More than half of our loans have a one-to-one match in HMDA. We use a conservative matching algorithm and so we have a great deal of confidence in the loans which we do match. The income, race, and ethnicity variables come from HMDA.[12] Distance to property is the distance between the location of the property and the location of the tax address (the location where the property tax bill will be sent) of the borrower. In some cases, this occurs when a household is moving to a new home and uses their old address as the tax address. In others it is because the property in question is the borrower's second home.[13] In the majority of cases this value is less than just a few miles as households move locally from one part of Los Angeles to another or are purchasing investment properties near to them. For almost all refinances, the distance is 0 as the refinancer also lives in the property. Cases where the value is non-zero are second homes.

Our second sample uses the data from the first sample and fills out the panel for every quarter between 2008Q1 and 2011Q4. We are left with a panel of more than 1,000,000 outstanding mortgages. To ensure the most complete sample we go back to 1990, the beginning of coverage in CoreLogic. Therefore, for each observation, unique at the property by quarter level, we know details of the outstanding mortgage loan, the borrowers, and whether or not they

[11] This is a heavier weighting to refinancing than normal due to the depressed housing market. Between 1990 and 2012 in Los Angeles, 70% of mortgage transactions were refinances.
[12] These variables serve as important controls, but our results are consistent across the CoreLogic mortgage data that does not match to HMDA.
[13] This definition is used to define households purchasing investment properties by Chinco and Mayer (2016)

refinance so long as the owner of the property moved in after 1990 (18 years before the time period on which we estimate our models). The characteristics of the outstanding loans are very similar to those presented in table 1. What we gain in this panel data is a household by quarter dummy variable indicating if the outstanding loan was refinanced or not. See more details of the refinancing rates and characteristics of the outstanding loans in Tables 10 and 11, respectively.

3.3 Neighbor Decisions

To identify social influence effects on a household we must construct measures of its neighbors' activities. In our first tests we explore the change in a household's propensity to choose a certain lender or lender type as a function of the choices its neighbors have made. For each geography (either census block or neighborhood) by quarter we define the share of outstanding loans that were originated by a certain lender. For example, if a block in Los Angeles has 36 outstanding loans and 4 of them were originated by credit unions, then the share of outstanding mortgages originated by credit unions is 1/9. We do this same exercise for the three largest lenders in Los Angeles by number of originated loans. These shares can be seen in Table 2, Panel A. To get some sense of the variance in neighbor share, we rank all blocks by the share of outstanding mortgages that have the given characteristic. We can see, for example, that the 10^{th} percentile block with respect to proportion of shares originated by Bank of America has a 0 percent share, whereas the median block has a 7.1 percent share.

Also presented in Table 2 are the shares of block neighbors whose loans have adjustable rates. It is the decision to choose an ARM or FRM that we explore in our second set of tests. The variation in ARM share across census blocks is economically large. Some blocks have very low levels of ARM share while in other areas more than half of the outstanding mortgages are adjustable rate loans.

In Table 12, we present the peer measures that we use for our refinancing tests. The measure we use here is, because of the different nature of the problem, constructed differently. We look at the same geographic levels as before and count the number of peer loans that are refinanced and divide that by the number of peer loans outstanding. We are careful not to include the household itself in these rates. So the proportion of peer households that have refinanced in the last time period are *household dependent*. To give a sense of the refinancing rates, though, Table 12 presents the raw proportions.

4 Results

4.1 Lender Choice

In Table 4 we use model (1) to estimate a household's propensity to choose the same lender when refinancing as their peers. We look at refinance loans only, and not purchase loans, because refinancing households have had a chance to interact with their neighbors and are subject to a social influence effect. Purchasers are new to the area and therefore not at risk for social influence. Looking at specification (2), we find that households are more likely to choose Wells Fargo as the proportion of their neighbors' outstanding loans with Wells Fargo increases, while controlling for proportion of their neighbors at the census block group level whose outstanding loans are with Wells Fargo. Note that these levels can be thought of as a wedding cake. I.e., the block loans are included in the neighborhood loans. So the block loan effect is over and above a neighborhood effect. The economic magnitude is meaningful. Increasing the share of outstanding block peers that have their loans with Wells Fargo from 0% to 15.8% increases the average refinancing household's likelihood of choosing Wells Fargo by (.0289 * .158) = .00457 percentage points, an increase of 3.49%. We choose 0% and 15.8% shares because this is the share of block peers that have Wells Fargo loans at the 10^{th} and 90^{th} percentile blocks, respectively, as seen in table 2.

Also in table 4 we look at credit unions, Bank of America, and JP Morgan Chase. In the first two cases we find that households are more likely to choose those types of lenders if their peers have. Specifically, performing the same calculations as before, we find that households are 3.68% more likely to choose a credit union and 2.72% more likely to choose Bank of America.[14]

[14] Credit unions: (.06 + (.021)*(.105 – 0))/(.06) – 1; Bank of America: (.125 + (.017)*(.20 – 0))/(.125) – 1

In table 5 we look at purchase loans and observe that there is no longer any social influence effect. This result is as expected. Note that in all cases the effect of greater neighborhood shares is correlated with higher likelihood of choosing the lender. This results is likely driven by endogenous group formation and correlated unobservables and demonstrates the necessity for our empirical strategy.

To better use all of the data, we estimate model (2) using the sample of all possible outstanding mortgage pairs. We then run a simple regression. Are households more likely to share the exact same lender (one of approximately 2500 in Los Angeles in our time period) if they live on the same block, given that they live in the same neighborhood? We present our results in Table 6. We find that a pair is nearly one percent more likely to share the exact same lender if they live on the same block.

4.2 Adjustable or Fixed

We next explore the second household decision, to pick an adjustable or fixed interest rate mortgage, in Table 7. We build the model by adding neighborhood share and then more restrictive fixed effects. Across specifications (2) through (5) our main result is remarkably consistent. We use specification (3) as our preferred specification since the inclusion of the geography fixed effects do not meaningfully change the results but are incredibly restrictive, especially in the following subsample analyses. As before we test on the sample of refinance loans. Specification (3) estimates that increasing the share of block peers who have ARMs from 0% to 62.5%, then 10th and 90th percentiles, respectively, increases a household's likelihood of choosing an ARM when they refinance by 1.67 percentage points. This represents an increase of 9% for the average household.

In table 8 we include demographic controls. The results from specification (1) to (2) are economically unchanged. In specifications (3) and (4) we estimate our model not with refinance loans, but with purchase loans. As expected, there are no significant block peer social interaction effects. CoreLogic loans with HMDA matches, and therefore demographic information, are systematically different than those without matches. We therefore prefer specifications (1) and

(3), which not only demonstrate the presence of social influence effects in refinances and not purchases, but also show a strikingly consistent neighborhood effect. This neighborhood effect is likely attributable to such features as loan availability and pricing and local macroeconomic conditions.

In table 9, we look at two groups of owners. The first group is owners who live more than ten miles away from the household, the second group live either very locally or, predominately, in the property. We find that, when refinancing, non-occupant owners are completely unaffected by a hyper local social influence while the owner occupants are. Interestingly, the neighborhood effects are no longer important for the distance owners. It could be the case that these buyers are not at all affected by the area around the property and, for example, choose lenders local to where they live and not near the property. Alternatively, this group of borrowers, owners who own property more than ten miles away from their primary residence, may be sufficiently different from the full sample that there is no correlation between their decisions. Further research should explore this result.

4.3 Refinance or Not

The third household decision where we test for the existence of social influence effects is the household's decision to refinance or not. We use our panel of households over time and model the probability that a household refinances in a given quarter on the share of their peers who have refinanced at some point in the previous six months. We present our key results in Table 13. We find that households are significantly more likely to refinance if their hyper local peers have recently refinanced. This effect over and above the effect at the neighborhood level. We find that the average household refinances in a given quarter with a 2.9% probability and this increases by .393 percentage points if the share of his block peers that have refinanced sometime in the previous six months increases from 0% to 13.8%. This is an increase of 13.56%.

There is a concern that, because household lender choice is affected by peers, that this is just a follow-up lender effect and not a social influence effect. We deal with this problem in table 14 specifications (3) and (4) by including just those households whose outstanding loans were originated by a lender that originated more than 50,000 loans (the 18 largest lenders). We then include 17 lender fixed effects in the model and the results remain unchanged. We take this as very strong evidence against the lender effect concern.

We provide our final piece of archival data evidence in Table 15. This is the result of our test that matches outstanding loans on a variety of characteristics. For each outstanding loan, we find a mortgage in a different census tract, but sharing a common specific lender, purpose (refinance or purchase), interest rate type (adjustable or fixed), quarters since the transaction, whether there was a co-applicant on the loan or not, the income quartile of the household, and the race of the first borrower listed on the loan. In the event that there are multiple matches, ties are broken based on the dollar amount of the outstanding loan and the incomes of the two households. Each pair is included in the sample only one time. We hypothesize that only the neighbors around the household will matter and not the neighbors of the match. This is exactly what we find.

4.4 Laboratory Evidence

Preliminary evidence demonstrated that participants who stayed in the same room or stayed in their first room for a majority of the time were significantly more likely to select the same mortgage as their peers from this first room (FRM in Room A, ARM in Room B). In contrast, participants who switched early were more likely to conform to the majority choice of their new peers in later trials (trial six and onwards) than those of their first peer group. By randomly assigning peer group, peer choice, and even varying moving/switching within the trial period, we find early causal evidence for social influence effects on mortgage decisions in even a laboratory setting.

5 Conclusion

We find that households making mortgage decisions are socially influenced by the decisions of their neighbors. We use household mortgage data, precisely geolocated real estate data, and a recently developed research design to identify the existence of social influence effects in three important household mortgage choices. Households are 2.7% to 3.7% more likely to choose a particular lender, 9% more likely to choose an adjustable rate mortgage (ARM), and 13.5% more likely to refinance if the share of their block-neighbors with that lender, with an ARM, or who have recently refinanced increases from the 10th percentile to the 90th percentile, respectively. Consistent with our findings, we document that distance movers are not initially affected by their new neighbors and that non-owner-occupied households never are. Finally, we complement our empirical strategies in the lab by experimentally assigning peers and peer decisions in a variety of ways.

Identifying the influence of peer effects and social influence in household mortgage decision-making has important implications both theoretically and substantively. Theoretically, we establish an issue of first order importance contributing to the fundamental understanding of what drives household decisions. Substantively, this work can be useful in improving consumer welfare. Based on our results, we can conclude that social influence might be driving individuals who may not have considered the refinancing decision to consider doing so, thereby saving consumers money in the long term. Alternatively, there may be areas where few households refinance because few of their peers have recently refinanced, creating a cycle of under refinancing. Future research should investigate the conditions in which peer effects and social influence may improve mortgage decisions and benefit consumers and also conditions where peer effects could hurt mortgage decisions and increase suboptimal behavior

Future work should also examine the role of expertise. Does financial expertise buffer individuals from the negative consequences of social influence? Or might it decrease the benefits that social influence may afford? Are unsophisticated households more influenced by nearby experts and can nearby experts play an important role in improving social welfare? By establishing the existence and importance of social influence in household mortgage decision making, we provide an important stepping stone and open the door for a number of areas of inquiry.

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Table 1: Summary statistics on mortgage loans originated in Los Angeles between 2008 and 2011. The sample consists of all mortgage loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses, and (2) own no more than one other property at that time. The sample is of loans originated between 2008Q1 and 2011Q4. Variables are defined as follows. Refinance means the loan is a refinance, as opposed to a purchase, loan. Adjustable rate mortgages are defined by dataquick and all mortgages have either adjustable or fixed interest rates. The loan-to-value variable is only defined for purchase loans with a known sale price. The bank, credit union, and mortgage company lender tags are defined by dataquick. These are not exclusive categorizations. I.e., a lender can be both a bank and Wells Fargo. Matched to HMDA equals 1 if the dataquick loan has a unique match in HMDA. Distance to property is the distance between the mailing address of the borrower and the property of the mortgage. Co-applicant indicates that there is more than one person on the mortgage contract. The income, race, and ethnicity variables are from HMDA.

	Mean	Std. dev.	Median	N
Panel A: Loan Characteristics				
Refinance (=1)	80.5%	39.6%		519,648
Adjustable Rate Mortgage (=1)	18.5%	38.8%		519,648
Loan Amount	329,799	254,681	292,477	519,648
Loan to Value (if purchase loan)	72.7%	30.2%	80.0%	101,313
Transaction Year 2008 (=1)	22.4%	41.7%		519,648
Transaction Year 2009 (=1)	24.2%	42.8%		519,648
Transaction Year 2010 (=1)	26.8%	44.3%		519,648
Transaction Year 2011 (=1)	26.6%	44.2%		519,648
Panel B: Lender Characteristics				
Bank Lender (=1)	49.8%	50.0%		519,648
Credit Union Lender (=1)	6.0%	23.8%		519,648
Mortgage Company Lender (=1)	22.6%	41.8%		519,648
Wells Fargo Lender (=1)	13.1%	33.8%		519,648
Bank of America Lender (=1)	12.5%	33.1%		519,648
JP Morgan Chase Lender (=1)	5.9%	23.5%		519,648
Panel C: Borrower Characteristics				
Matched to HMDA loan (=1)	58.8%	49.2%		519,648
Distance to Property (miles)	0.31	2.49	0.00	519,466
Co-applicant (=1)	51.1%	50.0%		519,648
Applicant Income (1,000s)	140.95	210.67	101.00	283,870
Race, Asian (=1)	13.8%	34.5%		305,632
Race, Black (=1)	3.8%	19.2%		305,632
Race, White (=1)	60.5%	48.9%		305,632
Ethnicity, Hispanic (=1)	18.0%	38.4%		305,632

Table 2. Proportion of outstanding loans in a geography that have a certain characteristic. Our sample includes approximately 75,000 census blocks and covers 16 time quarters, 2008Q1 – 2011Q4. Observations are unique at the block-by-quarter level. Read the table as follows. 39.9% of the outstanding loans at the average block-by-quarter observation are adjustable rate mortgages. And 3.6% of the loans were originated by a Credit Union. Block-by-quarter observations are ordered and the values at the 10th, 25th, 50th, 75th, and 90th percentile are given. In panels B, C, and D we look at one just the given quarter. In these samples, observations are unique at the block level.

	Mean	Std. dev.	10th	25th	Median	75th	90th	N
Panel A: Pooled								
Adjustable Rate Share	39.9%	21.2%	0.0%	29.4%	40.9%	50.0%	62.5%	1,216,704
Credit Union Share	3.6%	6.8%	0.0%	0.0%	0.0%	5.6%	10.5%	1,216,704
Wells Fargo Share	6.4%	9.6%	0.0%	0.0%	4.0%	9.6%	15.8%	1,216,704
Bank of America Share	8.8%	10.9%	0.0%	0.0%	7.1%	13.0%	20.0%	1,216,704
JP Morgan Chase Share	1.5%	4.2%	0.0%	0.0%	0.0%	0.0%	5.3%	1,216,704
Panel B: 2008Q1								
Adjustable Rate Share	42.8%	21.7%	0.0%	33.3%	44.4%	54.5%	66.7%	75,840
Credit Union Share	3.5%	6.6%	0.0%	0.0%	0.0%	5.6%	10.5%	75,840
Wells Fargo Share	5.9%	9.4%	0.0%	0.0%	3.4%	9.1%	14.8%	75,840
Bank of America Share	8.1%	10.5%	0.0%	0.0%	6.3%	12.5%	18.8%	75,840
JP Morgan Chase Share	1.1%	3.7%	0.0%	0.0%	0.0%	0.0%	4.2%	75,840
Panel C: 2009Q4								
Adjustable Rate Share	40.3%	21.1%	0.0%	30.0%	41.7%	50.0%	62.5%	76,051
Credit Union Share	3.6%	6.8%	0.0%	0.0%	0.0%	5.6%	10.6%	76,051
Wells Fargo Share	6.3%	9.6%	0.0%	0.0%	4.0%	9.5%	15.4%	76,051
Bank of America Share	8.8%	10.9%	0.0%	0.0%	7.1%	13.0%	20.0%	76,051
JP Morgan Chase Share	1.3%	4.0%	0.0%	0.0%	0.0%	0.0%	4.8%	76,051
Panel D: 2011Q4								
Adjustable Rate Share	36.3%	20.4%	0.0%	25.0%	36.8%	47.4%	57.1%	76,176
Credit Union Share	3.6%	6.8%	0.0%	0.0%	0.0%	5.6%	10.6%	76,176
Wells Fargo Share	6.9%	10.0%	0.0%	0.0%	4.8%	10.3%	16.7%	76,176
Bank of America Share	9.2%	11.1%	0.0%	0.0%	7.6%	13.6%	20.0%	76,176
JP Morgan Chase Share	2.1%	5.0%	0.0%	0.0%	0.0%	3.0%	6.8%	76,176

Interpretation: There is a significant variation across neighborhoods in the proportion of outstanding loans that have adjustable interest rates, the proportion of borrowers whose mortgages were originated by a credit union, and the proportion of borrowers whose mortgages were originated by Wells Fargo.

Table 3: Validity of Block versus Adjacent Block Neighbors Assumption. For every house purchased with a mortgage between 2008Q1 – 2011Q4, we compute the absolute value of the difference between the purchase loan / purchased property and the average of other houses on the block. We then compute the same difference but between the purchase loan and the average of houses in the adjacent blocks. These absolute values are averaged over all purchase loans and presented in columns 1 and 2. The third column presents the difference between these two values. A negative value means the house is less different from its block than its neighborhood. The fourth column tests whether this difference in differences is statistically different from zero. The two groups, block peers and group peers, are mutually exclusive.

	Average Absolute Value of Difference Between Purchased Household & Block	Average Absolute Value of Difference Between Purchased Household & Neighborhood	Difference in Differences	T-Test on Difference	N
Panel A: Buyer Characteristics					
Co-applicants (=1)	0.479	0.482	-0.003	-6.51	83,990
Income (1,000s USD)	64.849	62.126	2.723	13.14	60,390
Race, white (=1)	0.460	0.464	-0.004	-6.77	74,534
Second home (=1)	0.024	0.024	0.001	5.19	83,990
Panel B: Property Characteristics					
Year Built (years)	8.02	10.20	-2.179	-87.07	83,207
Square Feet	531	599	-67.752	-30.87	83,990
2012 Assessed Value (USD)	191,916.30	198,852.10	-6,935.77	-11.26	83,990

Interpretation: The difference in differences between a purchased home and the other homes on its block and a purchased home and the other homes on the adjacent blocks are not economically meaningful. This evidence supports the assumption that a household, conditional on choosing a certain census area, is randomly assigned a block. We will use both definitions of neighborhood – census block group and adjacent blocks – throughout the paper.

Table 4. Modelling a household's propensity to choose a lender as a function of the proportion of their peers who have chosen that same lender. Linear probability models. The sample consists of all refinance loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. Outstanding adjacent block loans include the outstanding loans in the block. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level. Standard errors are clustered at the census block level.

	dependent variable: new mortgage is the same as sample (=1)			
	(1)	(2)	(3)	(4)
sample, refinance loans from:	*Credit Union*	*Wells Fargo*	*Bank of America*	*JP Morgan Chase*
Share of all outstanding block loans originated by a Credit Union	0.0210*			
	(0.012)			
Share of all outstanding neighborhood loans originated by a Credit Union	0.723***			
	(0.022)			
Share of all outstanding block loans originated by Wells Fargo		0.0289**		
		(0.012)		
Share of all outstanding neighborhood loans originated by Wells Fargo		0.413***		
		(0.024)		
Share of all outstanding block loans originated by Bank of America			0.0170*	
			(0.009)	
Share of all outstanding neighborhood loans originated by Bank of America			0.186***	
			(0.021)	
Share of all outstanding block loans originated by JP Morgan Chase				0.0199
				(0.016)
Share of all outstanding neighborhood loans originated by JP Morgan Chase				-0.241***
				(0.039)
New Loan is an ARM (=1)	0.0470***	0.00780***	0.108***	-0.0330***
	(0.001)	(0.001)	(0.002)	(0.001)
Co-applicants (=1)	0.0176***	0.0142***	0.00948***	0.00418***
	(0.001)	(0.001)	(0.001)	(0.001)
Quarter Fixed Effects	Y	Y	Y	Y
N	417,520	417,520	417,520	417,520

Interpretation: Households are more likely to choose a certain lender type or lender if more people in their block have chosen that same lender type or lender. We control for the share in the neighborhood which includes the block itself and the adjacent blocks. Therefore, our block effect is the effect over and above the effect in the larger neighborhood. We call this effect a social influence effect. Note that in this and the previous table we look only at refinance loans.

Table 5. Modelling a household's propensity to choose a lender as a function of the proportion of their peers who have chosen that same lender. Linear probability models. The sample consists of all purchase loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. Outstanding adjacent block loans include the outstanding loans in the block. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level. Standard errors are clustered at the census block level.

	dependent variable: new mortgage is the same as sample (=1)			
	(1)	(2)	(3)	(4)
sample, purchase loans from:	*Credit Union*	*Wells Fargo*	*Bank of America*	*JP Morgan Chase*
Share of all outstanding block loans originated by a Credit Union	0.01			
	(0.011)			
Share of all outstanding neighborhood loans originated by a Credit Union	0.288***			
	(0.022)			
Share of all outstanding block loans originated by Wells Fargo		-0.0177		
		(0.018)		
Share of all outstanding neighborhood loans originated by Wells Fargo		0.438***		
		(0.037)		
Share of all outstanding block loans originated by Bank of America			0.007	
			(0.016)	
Share of all outstanding neighborhood loans originated by Bank of America			0.231***	
			(0.033)	
Share of all outstanding block loans originated by JP Morgan Chase				-0.00579
				(0.016)
Share of all outstanding neighborhood loans originated by JP Morgan Chase				0.135***
				(0.041)
New Loan is an ARM (=1)	0.0191***	0.00798**	-0.0227***	-0.000224
	(0.002)	(0.004)	(0.003)	(0.002)
Co-applicants (=1)	0.00757***	0.0162***	0.0143***	0.00240***
	(0.001)	(0.002)	(0.002)	(0.001)
Quarter Fixed Effects	Y	Y	Y	Y
N	101,071	101,071	101,071	101,071

Interpretation: There are no social influence effects operating on households taking out purchase loans. Households moving to a new area have not yet socially interacted with the inhabitants and so are not influenced at all by their decisions. We believe this result is in line with a social influence effect that operates at local level. Note that a household does behave similarly to the larger area to which its moving. This is because of a number of larger area-level effects that influence lender choice including, for example, availability, advertising, and prices.

Table 6. Modelling the likelihood a pair of households have the same lender if they live on the same block conditional on living in the same neighborhood. Linear probability models. All pairs of outstanding refinance loans between households who live in the same neighborhood are constructed. Households that also live on the same block are indicated with a dummy equal to 1. If two households have their outstanding loans from the same lender (there are approximately 2000 unique lenders in our sample) the pair receive another dummy equal to 1. We estimate the effect of living in the same block on having a mortgage loan from the same lender. The sample is all Los Angeles mortgages outstanding on January 1, 2011 that were originated between 2009Q1 – 2010Q4. All models use robust standard errors. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the group level and tract level, respectively.

	dependent variable: borrower pair has common lender (=1)
	(2)
sample	*borrower pairs in the same neighborhood*
Pair live on the same block	0.000884***
	(0.000136)
Tract Fixed Effects	Y
N	76,012,930

Interpretation: A pair of households are more likely to share a common lender if they live on the same block than if they live in the same neighborhood but not on the same block. This is evidence consistent with a social influence effect that operates at a very local level.

Table 7. Modelling a household's propensity to choose an ARM as a function of the proportion of their peers who have ARMs. Linear probability models. Dependent variable is a dummy equal to 1 if the loan is an ARM. The sample consists of all refinance loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. All loans were originated between 2008Q1-2011Q4. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

	dependent variable: new mortgage is an ARM (=1)				
	(1)	(2)	(3)	(4)	(5)
sample			*refinances*		
Share of all outstanding block loans with adjustable rates	0.273***	0.0252***	0.0266***	0.0142**	0.0222***
	(44.15)	(3.57)	(3.85)	(2.09)	(2.98)
Share of all outstanding neighborhood loans with adjustable rates		0.794***	0.575***	0.958***	0.0586**
		(56.060)	(37.170)	(54.960)	(2.370)
Bank Lender	0.195***	0.188***	0.167***	0.184***	0.163***
	(123.020)	(119.980)	(106.330)	(114.770)	(86.360)
Credit Union Lender	0.241***	0.236***	0.214***	0.241***	0.214***
	(75.370)	(74.200)	(67.620)	(74.540)	(59.670)
Mortgage Company Lender	0.0306***	0.0251***	0.0226***	0.0234***	0.0203***
	(19.230)	(15.680)	(13.780)	(14.130)	(10.210)
Outstanding Loan is an ARM (=1)	0.102***	0.0923***	0.0670***	0.0854***	0.0619***
	(62.840)	(57.870)	(42.390)	(53.710)	(34.930)
Co-applicants (=1)	-0.0112***	-0.0101***	-0.00317**	-0.00890***	-0.0025
	(-7.94)	(-7.22)	(-2.33)	(-6.19)	(-1.59)
Quarter Fixed Effects			Y		
Census Group Fixed Effects				Y	
Quarter-by-Group Fixed Effects					Y
N	328,386	328,386	328,386	328,250	309,483

Interpretation: Here, we define the larger neighborhood as the block and its adjacent blocks, as opposed to the block and its block group as we did in the previous table. Our results are robust to this alternative definition of neighborhood peers. Using our preferred specification, (3), we find that households are (.0266) * (.625 – 0) = 1.66 percentage points, or 4.2 percent more likely, to choose an ARM if the share of their peers with ARMs increases from the 10th percentile to the 90th percentile.

Table 8. Modelling a household's propensity to choose an ARM as a function of the proportion of their peers who have ARMs. Linear probability models. Dependent variable is a dummy equal to 1 if the loan is an ARM. The sample consists of all loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. All loans were originated between 2008Q1-2011Q4. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

	dependent variable: new mortgage is an ARM (=1)			
	(1)	(2)	(3)	(4)
sample	*refinances*		*purchase loans*	
Share of all outstanding block loans with adjustable rates	0.0266***	0.0194**	0.00753	0.0124
	(3.85)	(2.42)	(0.83)	(1.07)
Share of all outstanding neighborhood loans with adjustable rates	0.575***	0.487***	0.586***	0.609***
	(37.170)	(25.740)	(29.320)	(21.600)
Bank Lender	0.167***	0.106***	0.114***	0.0653***
	(106.330)	(56.960)	(51.260)	(22.840)
Credit Union Lender	0.214***	0.0617***	0.118***	0.0822***
	(67.620)	(19.040)	(14.560)	(8.570)
Mortgage Company Lender	0.0226***	0.0209***	0.0372***	0.0208***
	(13.780)	(10.940)	(21.980)	(7.920)
Outstanding Loan is an ARM (=1)	0.0670***	0.0699***		
	(42.390)	(37.040)		
Co-applicants (=1)	-0.00317**	-0.00647***	0.00225	-0.00988***
	(-2.33)	(-3.86)	(1.230)	(-3.95)
Quarter Fixed Effects	Y	Y	Y	Y
Income Quartile Controls		Y		Y
Race and Ethnicity Controls		Y		Y
N	328,386	180,590	101,071	58,666

Interpretation: We find that households who move to an area, i.e., those who are taking out purchase loans, are much less affected by a hyper local social influence. Households moving to a new area have not yet socially interacted with the inhabitants and so are not influenced by their decisions. We believe this result is in line with a social influence effect that operates at local level. Note that a household does behave similarly to the larger area to which its moving. This is because of a number of larger area-level effects that influence lender choice including, for example, availability, advertising, and prices. Including income and demographic controls does not qualitatively change the results.

Table 9. Testing for social influence in different types of borrowers. Linear probability models. Dependent variable is a dummy equal to 1 if the loan is an ARM. The sample consists of all refinance loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. All loans were originated between 2008Q1-2011Q4. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

	dependent variable: new mortgage is an ARM (=1)			
	(1)	(2)	(3)	(4)
sample	*owners more than 10 miles away*		*owners less than 2 miles away*	
Share of all outstanding block loans with adjustable rates	0.013	-0.0227	0.0273***	0.0211***
	(0.15)	(-0.21)	(3.92)	(2.61)
Share of all outstanding neighborhood loans with adjustable rates	-0.0547	-0.0302	0.581***	0.486***
	(-0.33)	(-0.14)	(37.280)	(25.530)
Bank Lender	0.191***	0.0563**	0.167***	0.107***
	(10.210)	(2.000)	(105.470)	(57.140)
Credit Union Lender	0.390***	-0.131*	0.213***	0.0620***
	(3.460)	(-1.85)	(67.230)	(19.060)
Mortgage Company Lender	0.0682***	0.0392	0.0222***	0.0210***
	(2.640)	(1.120)	(13.450)	(10.930)
Outstanding Loan is an ARM (=1)	0.129***	0.125***	0.0663***	0.0693***
	(5.380)	(3.750)	(41.680)	(36.500)
Co-applicants (=1)	-0.0116	-0.0342	-0.00317**	-0.00642***
	(-0.58)	(-1.35)	(-2.31)	(-3.80)
Quarter Fixed Effects	Y	Y	Y	Y
Income Quartile Controls		Y		Y
Race and Ethnicity Controls		Y		Y
N	1,511	690	323,831	178,338

Interpretation: We find that households who are refinancing a mortgage loan on a second home, i.e., those who do not live at the property, are much less affected by a hyper local social influence. Households who do not live in the area interact less with the inhabitants and so are not influenced by their decisions. This result is consistent with a social influence effect that operates at local level.

Table 10: Outstanding loans and refinance rates over time. The sample is all outstanding loans made to households owned by people (as opposed to trusts or businesses) who own no more than two properties. Loans originated before 1992 are not included in the sample as data collection efforts had not yet begun.

	Number of Outstanding Loans…	…percent of which refinanced
2008 Q1	1,308,277	2.85%
2008 Q2	1,309,071	2.54%
2008 Q3	1,309,788	1.39%
2008 Q4	1,310,485	1.02%
2009 Q1	1,311,097	1.84%
2009 Q2	1,311,894	2.41%
2009 Q3	1,312,658	1.92%
2009 Q4	1,313,933	1.83%
2010 Q1	1,314,698	1.55%
2010 Q2	1,315,648	1.53%
2010 Q3	1,317,031	2.51%
2010 Q4	1,318,853	3.15%
2011 Q1	1,319,922	2.13%
2011 Q2	1,320,857	1.55%
2011 Q3	1,322,373	2.20%
2011 Q4	1,324,027	2.92%

Table 11: Characteristics of the refinancing households. The sample is all households with outstanding loans owned by people (as opposed to trusts or businesses) who own no more than two properties. Loans originated before 1992 are not included in the sample as data collection efforts had not yet begun.

	Mean	Std. dev.	Median	N
Panel A: 2008Q1				
Refinance (=1)	2.9%			1,308,277
Outstanding Loan is an ARM (=1)	43.6%			704,865
Outstanding Loan is a Refinance (=1)	81%			1,296,274
Quarters Since Last Refinance/Purchase	17.51	17.54	11.00	1,296,274
Co-applicant (=1)	48.9%			1,308,277
Applicant Income (1,000s)	124.44	166.72	94.00	582,521
Distance to Property (miles)	6.96	104.48	0.00	41,459
Race, White (=1)	50.7%			634,535
Panel B: 2009Q4				
Refinance (=1)	1.8%			1,313,933
Outstanding Loan is an ARM (=1)	43.6%			707,464
Outstanding Loan is a Refinance (=1)	1			1,300,237
Quarters Since Last Refinance/Purchase	22.00	18.39	16.00	1,300,237
Co-applicant (=1)	48.4%			1,313,933
Applicant Income (1,000s)	124.68	172.64	94.00	607,995
Distance to Property (miles)	7.86	113.29	0.00	32,192
Race, White (=1)	51.9%			657,328
Panel A: 2011Q4				
Refinance (=1)	2.9%			1,324,027
Outstanding Loan is an ARM (=1)	41.2%			714,220
Outstanding Loan is a Refinance (=1)	1			1,308,766
Quarters Since Last Refinance/Purchase	26.26	20.24	22.00	1,308,766
Co-applicant (=1)	48.0%			1,324,027
Applicant Income (1,000s)	124.69	172.45	93.00	642,623
Distance to Property (miles)	8.53	117.38	0.00	46,034
Race, White (=1)	53.6%			690,290

Table 12: Proportion of loans refinanced during the previous 3 months, 6 months, or 12 months. We calculate the proportion of loans that have been recently refinanced. Observations are unique at the block-by-quarter level

	mean	std	p10	p25	p50	p75	p90
Proportion of Block Loans Refinanced During the Last 1 Quarter	2.53%	5.50%	0.0%	0.0%	0.0%	3.8%	7.7%
Proportion of Block Loans Refinanced During the Last 2 Quarters	5.07%	8.31%	0.0%	0.0%	2.2%	7.7%	13.8%
Proportion of Block Loans Refinanced During the Last 4 Quarters	10.21%	13.14%	0.0%	0.0%	6.9%	15.1%	25.0%

Interpretation: There is a significant variation across neighborhoods in the proportion of households that have recently refinanced. Observations are at the census block by quarter level.

Table 13: Household Propensity to Refinance their Mortgage if Their Neighbors Recently Have. Linear probability models. The dependent variable is a dummy equal to 1 if the outstanding loan is refinanced. The sample consists of all outstanding mortgage loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. The sample is a panel over the time span 2008Q1 – 2011Q4 and including all outstanding mortgages originated after 1992. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the household level.

	dependent variable: household refinanced this quarter (=1)				
	(1)	(2)	(3)	(4)	(5)
sample			*refinances*		
Share of all block loans that have refinanced in the last 2 quarters	0.136***	0.0290***	0.0285***	0.0217***	0.0260***
	(88.84)	(16.50)	(16.24)	(12.30)	(14.57)
Share of all neighborhood loans that have refinanced in the last 2 quarters		0.370***	0.424***	0.139***	0.153***
		(109.870)	(116.950)	(35.720)	(26.220)
Outstanding Loan in an ARM	-0.00789***	-0.00778***	-0.00806***	-0.00786***	-0.00807***
	(-64.87)	(-63.82)	(-66.29)	(-63.38)	(-65.26)
Outstanding Loan is a Refinance	-0.795***	-0.794***	-0.791***	-0.793***	-0.788***
	(-146.62)	(-146.77)	(-146.68)	(-149.94)	(-148.33)
Co-applicants (=1)	0.00529***	0.00427***	0.00409***	0.00316***	0.00327***
	(45.760)	(36.840)	(35.550)	(26.100)	(27.110)
Quarters Since Last Transaction FE	Y	Y	Y	Y	Y
Previous Lender Type FE	Y	Y	Y	Y	Y
Quarter Fixed Effects			Y		
Census Group Fixed Effects				Y	
Quarter-by-Group Fixed Effects					Y
N	10,985,347	10,985,347	10,985,347	10,985,345	10,984,645

Interpretation: The key refinancing result. A household is more likely to refinance as the share of its block neighbors who have recently refinanced increases, controlling for the share of larger neighborhood peer households who have recently refinanced. This result is robust to time, area, and time-by-area fixed effects.

Table 14: Household Propensity to Refinance their Mortgage if Their Neighbors Recently Have. Linear probability models. The dependent variable is a dummy equal to 1 if the outstanding loan is refinanced. The sample consists of all outstanding mortgage loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. The sample is a panel over the time span 2008Q1 – 2011Q4 and including all outstanding mortgages originated after 1992. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the household level.

	dependent variable: household refinanced this quarter (=1)			
	(1)	(2)	(3)	(4)
sample	*refinances*			
Share of all block loans that have refinanced in the last 2 quarters	0.0285***	0.0307***	0.0281***	0.0324***
	(16.24)	(10.80)	(11.54)	(8.16)
Share of all neighborhood loans that have refinanced in the last 2 quarters	0.424***	0.457***	0.405***	0.457***
	(116.950)	(78.260)	(79.770)	(55.610)
Outstanding Loan in an ARM	-0.00806***	-0.0124***	0.00273***	0.00181***
	(-66.29)	(-62.04)	(15.750)	(6.210)
Outstanding Loan is a Refinance	-0.791***	-0.845***	-0.705***	-0.825***
	(-146.68)	(-165.50)	(-87.55)	(-96.69)
Co-applicants (=1)	0.00409***	0.00589***	0.00418***	0.00815***
	(35.550)	(30.950)	(25.660)	(29.800)
Quarters Since Last Transaction FE	Y	Y	Y	Y
Previous Lender Type FE	Y	Y		
Originator of Outstanding Loan FE			Y	Y
Quarter Fixed Effects	Y	Y	Y	Y
Race & Income Controls		Y		Y
N	10,985,347	4,768,915	5,582,289	2,421,770

Interpretation: The key refinancing result is robust to controlling demographic controls. In specifications (3) and (4) we include 18 lender fixed effects on a sample that includes only those 18 lenders with more than 50,000 mortgage originations. The results remain unchanged.

Table 15: Falsification test, households in different census tracts matched on observables. These specifications are identical to those in model (3) from the previous table. The sample is constructed by taking a random sample of outstanding loans and finding them a match. After selecting 1,000,000 outstanding loan-quarters from the sample we match it to a mortgage *in a different census tract*, but sharing a common exact lender (in models (3) and (4)), purpose (refinance or purchase), interest rate type (adjustable or fixed), quarters since the outstanding loan's origination, whether there was a co-applicant on the loan or not, the income quartile of the household, and the race of the first borrower listed on the loan. In the event that there are multiple matches, ties are broken based on the dollar amount of the outstanding loan and the incomes of the two households. We are left with a sample of approximately 500,000 outstanding loans and their matches. We then model the relationship between a household's likeliness to refinance and the refinancing rates of its peers *and the refinancing rates of its match's peers*. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. All models use robust standard errors.

	dependent variable: household refinanced this quarter (=1)			
	(1)	(2)	(3)	(4)
sample	*all matches*		*matched on exact same lender*	
	original household	*matched household*	*original household*	*matched household*
Proportion of Loans on the Household's Block Refinanced During the Last 2 Quarters	0.0357***	-0.00387	0.0337***	-0.0116
	(3.930)	(-0.45)	(2.880)	(-1.07)
Proportion of Loans in the Household's Neighborhood Refinanced During the Last 2 Quarters	0.457***	0.0482***	0.480***	0.0855***
	(24.790)	(2.670)	(19.750)	(3.650)
Proportion of Loans on the Household's Match's Block Refinanced During the Last 2 Quarters	0.00573	0.0377***	-0.00231	0.0521***
	(0.630)	(3.930)	(-0.19)	(4.130)
Proportion of Loans in the Household's Match's Neighborhood Refinanced During the Last 2 Quarters	0.0216	0.461***	0.036	0.464***
	(1.200)	(24.980)	(1.500)	(19.260)
Matching Variable Controls	Y	Y	Y	Y
N	418,970	418,970	250,358	250,358

Interpretation: Using a matching method, we control for many observable characteristics of the outstanding loans and their borrowers. We find that households behave like their peers, but not the peers of the matched household whose loan has the same characteristics. We use this result to rule out several alternative hypotheses – most importantly a lender fixed effect. Specifically, the results are the strongest in models (3) and (4) where we force the matched pair to have their outstanding loans with the exact same lender.

Table A1: Validity of Block versus Group Neighbors Assumption. For every house purchased with a mortgage between 2008Q1 – 2011Q4, we compute the absolute value of the difference between the purchase loan / purchased property and the average of other houses on the block. We then compute the same difference but between the purchase loan and the average of houses in the census group, i.e., houses in the census group but not on the block. These absolute values are averaged over all purchase loans and presented in columns 1 and 2. The third column presents the difference between these two values. A negative value means the house is less different from its block than its neighborhood. The fourth column tests whether this difference in differences is statistically different from zero. The two groups, block peers and group peers, are mutually exclusive.

	Average Absolute Value of Difference Between Purchased Household & Block	Average Absolute Value of Difference Between Purchased Household & Group	Difference in Differences	T-Test on Difference	N
Panel A: Buyer Characteristics					
Co-applicants (=1)	0.479	0.482	-0.004	-7.91	83,963
Income (1,000s USD)	64.851	62.281	2.570	12.27	60,365
Race, white (=1)	0.460	0.464	-0.003	-6.95	74,511
Second home (=1)	0.024	0.024	0.000	-0.19	83,963
Panel B: Property Characteristics					
Year Built (years)	8.02	10.76	-2.748	-98.56	83,180
Square Feet	529	628	-98.615	-43.36	83,963
2012 Assessed Value (USD)	191,569.30	201,994.30	-10,424.95	-16.69	83,963

Interpretation: The difference in differences between a purchased home and the other homes on its block and a purchased home and the other homes in its census block group are not economically meaningful. This evidence supports the assumption that a household, conditional on choosing a certain census block group, is randomly assigned a block.

Table A2. Modelling a household's propensity to choose a lender as a function of the proportion of their peers who have chosen that same lender. Linear probability models. The sample consists of all refinance loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. Outstanding group loans include the outstanding loans in the block. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

	dependent variable: new mortgage is the same as sample (=1)			
	(1)	(2)	(3)	(4)
sample, refinance loans from:	*Credit Union*	*Wells Fargo*	*Bank of America*	*JP Morgan Chase*
Share of all outstanding block loans originated by a Credit Union	0.0313***			
	(0.011)			
Share of all outstanding group loans originated by a Credit Union	0.825***			
	(0.023)			
Share of all outstanding block loans originated by Wells Fargo		0.0378***		
		(0.012)		
Share of all outstanding group loans originated by Wells Fargo		0.468***		
		(0.026)		
Share of all outstanding block loans originated by Bank of America			0.0157*	
			(0.009)	
Share of all outstanding group loans originated by Bank of America			0.245***	
			(0.023)	
Share of all outstanding block loans originated by JP Morgan Chase				0.0217
				(0.015)
Share of all outstanding group loans originated by JP Morgan Chase				-0.358***
				(0.045)
New Loan is an ARM (=1)	0.0473***	0.00739***	0.108***	-0.0329***
	(0.001)	(0.001)	(0.002)	(0.001)
Co-applicants (=1)	0.0172***	0.0141***	0.00945***	0.00424***
	(0.001)	(0.001)	(0.001)	(0.001)
Quarter Fixed Effects	Y	Y	Y	Y
N	417,520	417,520	417,520	417,520

Interpretation: In column 1, we see that a household is more likely to choose a credit union when refinancing as the share of households on its block who have their loans with credit unions increases. Recall that the 10th percentile of credit union share is 0% and the 90th percentile is 10.5%. So moving a household from a 10th percentile credit union share block to a 90th percentile credit union share block increases its probability of choosing a credit union by (.105-0) * (.0313) = .0033 percentage points – an increase of 9.5 percent from an average rate of 3.6 percent. Magnitudes for the other lender choices can be similarly determined. We use these three lenders because they are the largest lenders in terms of number of originated mortgages.

Table A3. Modelling a household's propensity to choose a lender as a function of the proportion of their peers who have chosen that same lender. Linear probability models. The sample consists of all purchase loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. Outstanding group loans include the outstanding loans in the block. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

	dependent variable: new mortgage is the same as sample (=1)			
	(1)	(2)	(3)	(4)
sample, purchase loans from:	*Credit Union*	*Wells Fargo*	*Bank of America*	*JP Morgan Chase*
Share of all outstanding block loans originated by a Credit Union	0.014			
	(0.011)			
Share of all outstanding group loans originated by a Credit Union	0.326***			
	(0.023)			
Share of all outstanding block loans originated by Wells Fargo		-0.013		
		(0.018)		
Share of all outstanding group loans originated by Wells Fargo		0.518***		
		(0.040)		
Share of all outstanding block loans originated by Bank of America			0.010	
			(0.015)	
Share of all outstanding group loans originated by Bank of America			0.266***	
			(0.036)	
Share of all outstanding block loans originated by JP Morgan Chase				0.00222
				(0.016)
Share of all outstanding group loans originated by JP Morgan Chase				0.145***
				(0.045)
New Loan is an ARM (=1)	0.0194***	0.00697*	-0.0228***	-0.000265
	(0.002)	(0.004)	(0.003)	(0.002)
Co-applicants (=1)	0.00732***	0.0157***	0.0143***	0.00239***
	(0.001)	(0.002)	(0.002)	(0.001)
Quarter Fixed Effects	Y	Y	Y	Y
N	101,071	101,071	101,071	101,071

Interpretation: There are no social influence effects operating on households taking out purchase loans. Households moving to a new area have not yet socially interacted with the inhabitants and so are not influenced at all by their decisions. We believe this result is in line with a social influence effect that operates at local level. Note that a household does behave similarly to the larger area to which its moving. This is because of a number of larger area-level effects that influence lender choice including, for example, availability, advertising, and prices.

Table A4. Modelling the likelihood a pair of households have the same lender if they live on the same block conditional on living in the same neighborhood. Linear probability models. All pairs of outstanding refinance loans between households who live in the same neighborhood are constructed. Households that also live on the same block are indicated with a dummy equal to 1. If two households have their outstanding loans from the same lender (there are approximately 2000 unique lenders in our sample) the pair receive another dummy equal to 1. We estimate the effect of living in the same block on having a mortgage loan from the same lender. The sample is all Los Angeles mortgages outstanding on January 1, 2011 that were originated between 2009Q1 – 2010Q4. All models use robust standard errors. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the group level and tract level, respectively.

	dependent variable: borrower pair has common lender (=1)
	(1)
sample	*borrower pairs in the same census block group*
Pair live on the same block	0.00110***
	(0.000155)
Group Fixed Effects	Y
N	117,968,992

Interpretation: A pair of households are more likely to share a common lender if they live on the same block than if they live in the same neighborhood but not on the same block. This is evidence consistent with a social influence effect that operates at a very local level.

Table A5. Modelling a household's propensity to choose an ARM as a function of the proportion of their peers who have ARMs. Linear probability models. Dependent variable is a dummy equal to 1 if the loan is an ARM. The sample consists of all refinance loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. All loans were originated between 2008Q1-2011Q4. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the group level and tract level, respectively.

	dependent variable: new mortgage is an ARM (=1)				
	(1)	(2)	(3)	(4)	(5)
sample			*refinances*		
Share of all outstanding block loans with adjustable rates	0.273***	0.0379***	0.0352***	0.0216***	0.0274***
	(44.15)	(5.52)	(5.27)	(3.33)	(3.82)
Share of all outstanding group loans with adjustable rates		0.865***	0.640***	1.703***	
		(57.520)	(39.030)	(73.810)	
Bank Lender	0.195***	0.187***	0.167***	0.177***	0.163***
	(123.020)	(119.130)	(106.190)	(109.860)	(86.360)
Credit Union Lender	0.241***	0.236***	0.214***	0.232***	0.214***
	(75.370)	(74.010)	(67.630)	(72.020)	(59.660)
Mortgage Company Lender	0.0306***	0.0243***	0.0223***	0.0177***	0.0203***
	(19.230)	(15.180)	(13.620)	(10.580)	(10.210)
Outstanding Loan is an ARM (=1)	0.102***	0.0912***	0.0664***	0.0803***	0.0619***
	(62.840)	(57.250)	(42.180)	(50.470)	(34.940)
Co-applicants (=1)	-0.0112***	-0.00987***	-0.00299**	-0.00885***	-0.00248
	(-7.94)	(-7.05)	(-2.20)	(-6.18)	(-1.58)
Quarter Fixed Effects			Y		
Census Group Fixed Effects				Y	
Quarter-by-Group Fixed Effects					Y
N	328,386	328,386	328,386	328,250	309,483

Interpretation: Households are more likely to choose ARMs if their hyper local peers have ARMs. This result is robust to the includes of time, area, and time-by-area fixed effects.

Table A6. Modelling a household's propensity to choose an ARM as a function of the proportion of their peers who have ARMs. Linear probability models. Dependent variable is a dummy equal to 1 if the loan is an ARM. The sample consists of all loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. All loans were originated between 2008Q1-2011Q4. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

	dependent variable: new mortgage is an ARM (=1)			
	(1)	(2)	(3)	(4)
sample	*refinances*		*purchase loans*	
Share of all outstanding block loans with adjustable rates	0.0352***	0.0283***	0.0206**	0.0266**
	(5.27)	(3.64)	(2.37)	(2.38)
Share of all outstanding group loans with adjustable rates	0.640***	0.545***	0.653***	0.685***
	(39.030)	(26.950)	(30.880)	(23.120)
Bank Lender	0.167***	0.105***	0.113***	0.0649***
	(106.190)	(56.820)	(51.140)	(22.740)
Credit Union Lender	0.214***	0.0618***	0.118***	0.0820***
	(67.630)	(19.070)	(14.550)	(8.580)
Mortgage Company Lender	0.0223***	0.0206***	0.0375***	0.0206***
	(13.620)	(10.770)	(22.080)	(7.850)
Outstanding Loan is an ARM (=1)	0.0664***	0.0697***		
	(42.180)	(37.000)		
Co-applicants (=1)	-0.00299**	-0.00598***	0.00238	-0.00882***
	(-2.20)	(-3.58)	(1.300)	(-3.52)
Quarter Fixed Effects	Y	Y	Y	Y
Income Quartile Controls		Y		Y
Race and Ethnicity Controls		Y		Y
N	328,386	180,590	101,071	58,666

Interpretation: We find that households who move to an area, i.e., those who are taking out purchase loans, are much less affected by a hyper local social influence. Households moving to a new area have not yet socially interacted with the inhabitants and so are not influenced by their decisions. We believe this result is in line with a social influence effect that operates at local level. Note that a household does behave similarly to the larger area to which its moving. This is because of a number of larger area-level effects that influence lender choice including, for example, availability, advertising, and prices. Including income and demographic controls does not qualitatively change the results.

Table A7. Testing for social influence in different types of borrowers. Linear probability models. Dependent variable is a dummy equal to 1 if the loan is an ARM. The sample consists of all refinance loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. All loans were originated between 2008Q1-2011Q4. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

	dependent variable: new mortgage is an ARM (=1)			
	(1)	(2)	(3)	(4)
sample	*owners more than 10 miles away*		*owners less than 2 miles away*	
Share of all outstanding block loans with adjustable rates	-0.0225	-0.0505	0.0361***	0.0300***
	(-0.26)	(-0.47)	(5.37)	(3.82)
Share of all outstanding group loans with adjustable rates	0.112	0.127	0.646***	0.544***
	(0.640)	(0.520)	(39.140)	(26.750)
Bank Lender	0.190***	0.0567**	0.167***	0.106***
	(10.200)	(2.010)	(105.320)	(57.000)
Credit Union Lender	0.387***	-0.134**	0.213***	0.0621***
	(3.420)	(-1.99)	(67.240)	(19.090)
Mortgage Company Lender	0.0680***	0.0398	0.0219***	0.0206***
	(2.630)	(1.140)	(13.270)	(10.750)
Outstanding Loan is an ARM (=1)	0.128***	0.124***	0.0657***	0.0691***
	(5.310)	(3.730)	(41.480)	(36.460)
Co-applicants (=1)	-0.0114	-0.0337	-0.00299**	-0.00593***
	(-0.57)	(-1.33)	(-2.18)	(-3.52)
Quarter Fixed Effects	Y	Y	Y	Y
Income Quartile Controls		Y		Y
Race and Ethnicity Controls		Y		Y
N	1,511	690	323,831	178,338

Interpretation: We find that households who are refinancing a mortgage loan on a second home, i.e., those who do not live at the property, are much less affected by a hyper local social influence. Households who do not live in the area interact less with the inhabitants and so are not influenced by their decisions. This result is consistent with a social influence effect that operates at local level.

Table A8: Household Propensity to Refinance their Mortgage if Their Neighbors Recently Have. Linear probability models. The dependent variable is a dummy equal to 1 if the outstanding loan is refinanced. The sample consists of all outstanding mortgage loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. The sample is a panel over the time span 2008Q1 – 2011Q4 and including all outstanding mortgages originated after 1992. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the household level.

	dependent variable: household refinanced this quarter (=1)				
	(1)	(2)	(3)	(4)	(5)
sample			*refinances*		
Share of all block loans that have refinanced in the last 2 quarters	0.136***	0.0416***	0.0417***	0.0414***	0.0407***
	(88.84)	(24.40)	(24.52)	(24.23)	(23.84)
Share of all group loans that have refinanced in the last 2 quarters		0.387***	0.455***	0.0650***	
		(110.950)	(119.690)	(14.970)	
Outstanding Loan in an ARM	-0.00789***	-0.00778***	-0.00806***	-0.00787***	-0.00807***
	(-64.87)	(-63.77)	(-66.26)	(-63.49)	(-65.31)
Outstanding Loan is a Refinance	-0.795***	-0.794***	-0.791***	-0.793***	-0.788***
	(-146.62)	(-146.75)	(-146.67)	(-149.92)	(-148.31)
Co-applicants (=1)	0.00529***	0.00433***	0.00412***	0.00324***	0.00337***
	(45.760)	(37.360)	(35.790)	(26.720)	(27.930)
Quarters Since Last Transaction FE	Y	Y	Y	Y	Y
Previous Lender Type FE	Y	Y	Y	Y	Y
Quarter Fixed Effects			Y		
Census Group Fixed Effects				Y	
Quarter-by-Group Fixed Effects					Y
N	10,985,347	10,985,347	10,985,347	10,985,345	10,984,645

Interpretation: The key refinancing result. A household is more likely to refinance as the share of its block neighbors who have recently refinanced increases, controlling for the share of larger neighborhood peer households who have recently refinanced. This result is robust to time, area, and time-by-area fixed effects. In specification (3), we find that a household is (.0417) * (.138 – 0) = .00575 percentage points, or 11.4 percent, more likely to refinance.

Table A9: Household Propensity to Refinance their Mortgage if Their Neighbors Recently Have. Linear probability models. The dependent variable is a dummy equal to 1 if the outstanding loan is refinanced. The sample consists of all outstanding mortgage loans made to households in Los Angeles County who are both (1) tagged as people, as opposed to trusts or businesses and (2) own no more than one other property at the time. The sample is a panel over the time span 2008Q1 – 2011Q4 and including all outstanding mortgages originated after 1992. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the household level.

	dependent variable: household refinanced this quarter (=1)			
	(1)	(2)	(3)	(4)
sample	*refinances*			
Share of all block loans that have refinanced in the last 2 quarters	0.0417***	0.0434***	0.0411***	0.0457***
	(24.52)	(15.79)	(17.37)	(11.85)
Share of all group loans that have refinanced in the last 2 quarters	0.455***	0.504***	0.434***	0.502***
	(119.690)	(81.340)	(81.850)	(57.470)
Outstanding Loan in an ARM	-0.00806***	-0.0123***	0.00270***	0.00181***
	(-66.26)	(-61.77)	(15.550)	(6.220)
Outstanding Loan is a Refinance	-0.791***	-0.845***	-0.705***	-0.825***
	(-146.67)	(-165.62)	(-87.54)	(-96.78)
Co-applicants (=1)	0.00412***	0.00596***	0.00422***	0.00824***
	(35.790)	(31.340)	(25.910)	(30.120)
Quarters Since Last Transaction FE	Y	Y	Y	Y
Previous Lender Type FE	Y	Y		
Originator of Outstanding Loan FE			Y	Y
Quarter Fixed Effects	Y	Y	Y	Y
Race & Income Controls		Y		Y
N	10,985,347	4,768,915	5,582,289	2,421,770

Interpretation: The key refinancing result is robust to controlling demographic controls. In specifications (3) and (4) we include 18 lender fixed effects on a sample that includes only those 18 lenders with more than 50,000 mortgage originations. The results remain unchanged.