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

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Abstract

We find evidence that neighbors apply an important economic force on households’ mortgage choices. 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. We test for social influence by estimating the effect of hyperlocal block peers (i.e., neighbors living on the same block) over and above the effect of neighborhood peers (i.e., neighbors living on the same or adjacent blocks). Assuming that households can choose in which neighborhood to live but not on which specific block, block peers, conditional on neighborhood peers, are as if randomly assigned. We find that households are 2% to 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 who own but do not occupy second and third homes. We find that movers are not initially affected by their hyperlocal peers, but become so over time. Non-occupant owners' decisions about their second and third properties are never influenced by the households that live around the property but are influenced by the neighbors at their primary residence, even when their primary residence is miles away from their second or third home. 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

Decisions surrounding household mortgage choices have a substantial impact at both the policy and individual household level. Mortgage decisions played a crucial role in precipitating the Great Recession, and thus there is a significant push to better understand the drivers of mortgage choices. Theory suggests that households making mortgage decisions consider their private personal characteristics (e.g., their likelihood of moving in the near future or their risk tolerance) and the pricing and terms of the available mortgage options (Agarwal, Driscoll, and Laibson (2013); Campbell and Cocco (2003); Coulibaly and Li (2009)). Social influence is recognized as a critical factor in many important consumption and labor decisions (Bayer, Ross, and Topa (2008); Goolsbee and Klenow (2002); Grinblatt, Keloharju and Ikäheimo (2008)). Results from a 2015 Consumer Financial Protection Bureau (CFPB) survey of two thousand borrowers who purchased homes in 2013 confirm the potential importance of social influence with half of respondents citing friends, relatives, and co-workers as important sources of information (CFPB, 2015). Yet little empirical research exists on how social connections influence mortgage choices.

In this paper we document the role of social influence, specifically focusing on the influence of a household's hyperlocal neighborhood peers, on several key mortgage decisions: lender choice, the choice of mortgage type (FRM or ARM), and the decision to refinance. 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 all mortgage loans in Los Angeles between 1990 and 2012, combined with a dataset of geolocated real estate data with the latitude and longitude of each house. This level of detail allows us to use a powerful research design that identifies social influence by estimating the effects of hyperlocal 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).[2] We find that households are 2% to 5% more likely to choose a particular lender, 1.5%

[2] 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.

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. We further leverage our detailed dataset by using movers and second property homeowners to rule out a variety of alternative hypotheses. Based on these findings, we propose that a household's block peers can be an important economic force on households' mortgage choices.

The key assumption in our methodology is that households may choose particular neighborhoods to live in, but are less likely to choose (or even 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). Figure 1 presents an example of our identification strategy. 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.

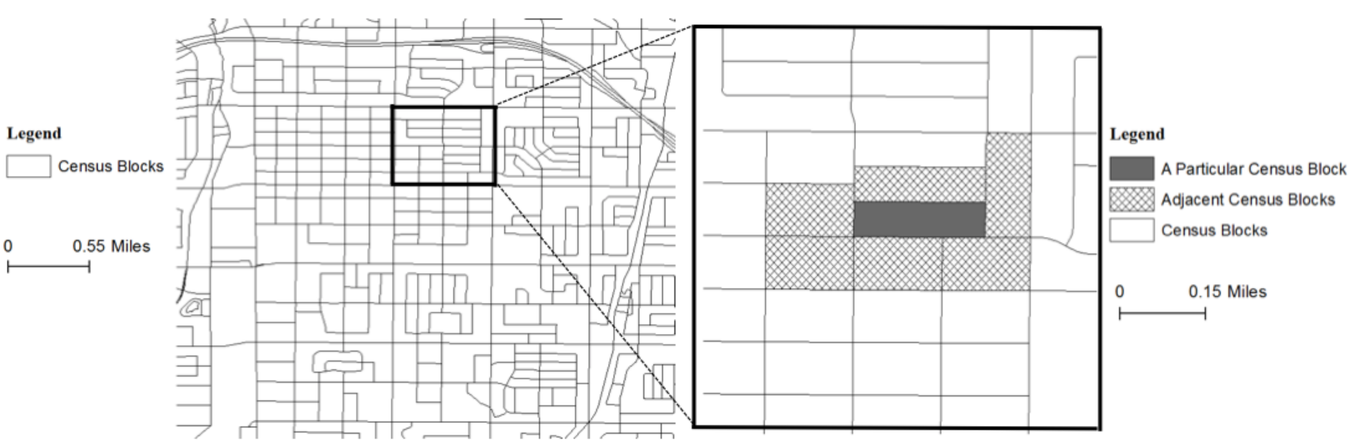

Figure 1: Census block delineations and adjacent polygon neighborhood example in Los Angeles. This left side of this figure presents census blocks in a northern part of Los Angeles. Los Angeles census blocks correspond closely to city blocks and are inhabited by an average of 25 households. This right side of this figure presents a zoomed in view of the census block and the adjacent census blocks. Combined, these make up a neighborhood. The average neighborhood in Los Angeles is made up of 9 blocks. For more information on how census blocks are constructed see https://www2.census.gov/geo/pdfs/reference/GARM/Ch11GARM.pdf.

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. The richness of our dataset also 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. In short, hyperlocal social influence effects matter in household mortgage decisions. And because these mortgage decisions are not easily observable publicly, we hypothesize that these social influence effects operate through word-of-mouth transmission.

To paint a more complete picture and to rule out a variety of alternative hypotheses, we apply our identification strategy to two subsamples: households moving to new neighborhoods and households that own second and third properties they do not occupy. Given that these groups have not lived by their neighbors, and have therefore not had a chance to be social influenced by them, we expect to find no social influence effects. Indeed, this is what we find. Specifically, we find that the lender choice and ARM decision of households moving to new areas are not affected by the decisions of their new block peers. Furthermore, households we see purchase a home in a new neighborhood and then refinance as occupants are initially unaffected by hyperlocal social influence but when they subsequently refinance are socially influenced. This result is consistent with a social influence effect that takes time, and a chance for social interactions to occur, to become economically important. 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 the property. Convincingly, non-occupant owners do behave like the block peers around the properties where they *do* currently live, even when their primary residences and their second and third homes are in different neighborhoods. Finally, the refinance decisions of non-owner-occupied properties are entirely unaffected by the refinance decisions of the other households living around the property.

We use two other empirical strategies to confirm our results. First, 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. This test allows us to use all loans in our sample, even those originated by small lenders. Second, 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. This test allows us to conclude the lender effects or other loan-specific effects are not causing the effects we document in our primary tests.

While we can conclude that these social influence effects are important, 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 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 brings to the literature a careful study using a universal sample of homeowners. Unlike previous work, we explore multiple household mortgage decisions in the same sample allowing us to conclude 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, which is likely larger than any of the estimates produced by extant research. 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.

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 households to 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.[3] There are at least two reasons to assume the assumption is valid. First, households might be indifferent between properties located on adjacent blocks. Second, property availability constraints mean that buyers might not have the option to live on a specific block in their desired neighborhood.

[3] 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.

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.

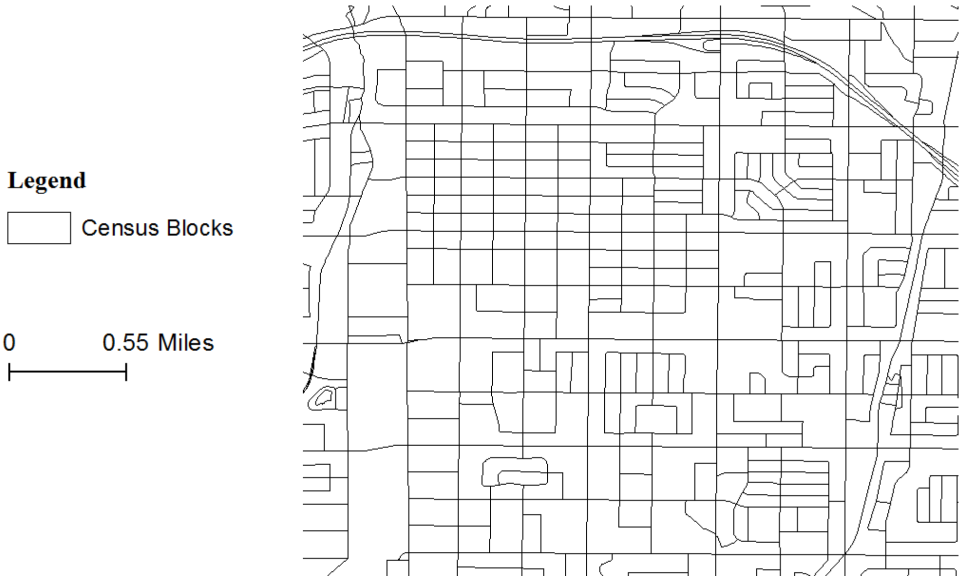

Figure 2: Census block delineations in Los Angeles. This figure presents census blocks in a northern part of Los Angeles. For more information on how census blocks are constructed see https://www2.census.gov/geo/pdfs/reference/GARM/Ch11GARM.pdf.

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.

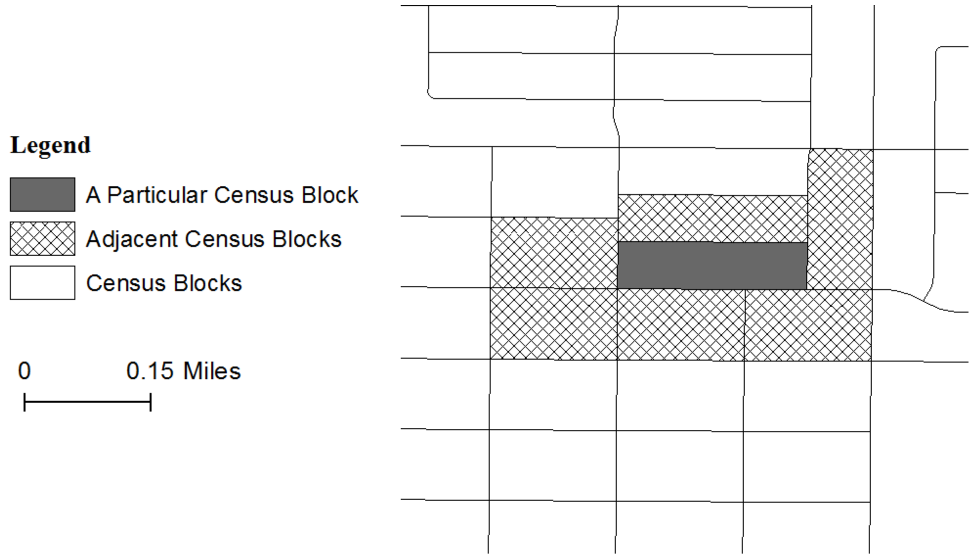

Figure 3: Adjacent Polygon Neighborhood Example. This figure presents a census block and the adjacent census blocks. Combined, these make up a neighborhood. The average neighborhood in Los Angeles is made up of 9 blocks.

The example of the Jones family is clearly contrived. We use it to illustrate the plausibility of our assumption that households first choose neighborhoods and then choose 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 valid. 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 non-randomly 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 estimates 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 block peers are perfectly randomly assigned, then our models cleanly identify 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 and third homes, to provide some compelling supportive evidence. Analysis of each subsample provides 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 their new peers after they have lived there and had time to interact and be socially influenced. This test is particularly compelling because many of the unobserved household characteristics are now no longer a concern. Households wealthy enough to purchase second homes, whether for investment or 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.

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 sometimes abstract 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.

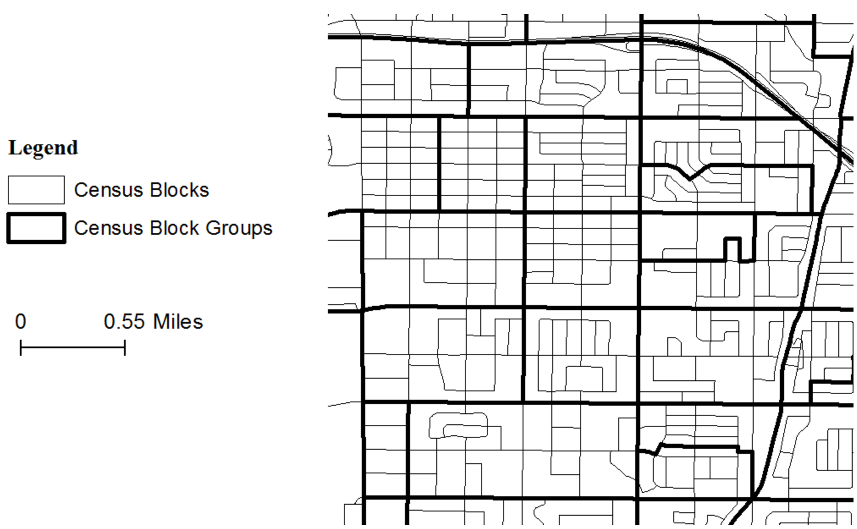

Figure 4: Census block group delineations in Los Angeles. This figure presents census blocks in a northern part of Los Angeles. Outline in a thick, black border are census block groups, the second smallest geographic delineation used by the Census.

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 our key tests using this measure of neighborhood. These results can be found in the online appendix.

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 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. We focus our attention on the time period between 2008 and 2011. We specifically use this period in order to avoid the bubble period and subsequent collapse of 2002 – 2007, given that a bubble is 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 two other properties assuming that if the owner of a property owns more than three properties at one time is not what we are thinking of when we say household.[4] 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.

Approximately 80% of the loans in our sample are refinance loans and 20% have adjustable interest rates.[5] 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.

[4]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.
[5] 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.

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 that are matched. The income, race, and ethnicity variables come from HMDA.[6] 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.[7] 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 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 13 and 14, 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

[6] These variables serve as important controls, but our results are consistent across the CoreLogic mortgage data that does not match to HMDA.
[7] This definition is used to define households purchasing investment properties by Chinco and Mayer (2016)

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 15, 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 15 presents the raw proportions.

4 Results

4.1 Lender Choice

In Table 4 we use our baseline model to estimate a household's propensity to choose Wells Fargo when refinancing as a function of the share of their peers who have their loans with Wells Fargo. 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 specifications (2) through (5), 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 neighborhood peers 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. We find that increasing the share of block peers with mortgages originated by Wells Fargo by ten percentage points increases the average household's propensity of choosing Wells Fargo by 3.17%.

In table 5 we also 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 4.95% more likely to choose a credit union and 2.04% more likely to choose Bank of America. In table 6 we look at purchase loans and observe that there is no longer any social influence effect. This result is expected. Note that in all cases the effect of greater neighborhood shares is correlated with higher likelihood of choosing the lender. This result 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 7. We find that a pair is approximately 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 8. 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 with adjustable rate mortgages by ten percentage points increases the average household's propensity of choosing an adjustable rate by 1.48%.

In table 9 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 10, we look at two groups of owners, those that do not occupy their property and those that do. The first group is owners whose mailing address zip code is different than the zip code of the property. For the second group, these zip codes are the same. We find that, when refinancing, non-occupant owners are completely unaffected by a hyper local social influence while the owner occupants are. In table 11, we ask if these non-occupant owners are influenced by the neighbors around their primary residence. It is these peers that the household most likely interacts with and is potentially socially influenced by. What we find is compelling. Borrowers are influenced by their hyperlocal peers even when making decisions about an investment property or second home in a completely different neighborhood. This result cannot be explained by the any of the alternative explanations that relate to local area effects like lender advertising. Finally, in table 12, we explore the set of households that (1) use a mailing zip code different from the property zip code when purchasing and (2) later refinance that loan. Some of these borrowers remain non-occupants, but many, when refinancing, now use the same mailing zip code as the property. We find that when purchasing there is no hyperlocal social influence effect nor is there a social influence for households that refinance as non-occupants. But for those households who moved to the property, hyperlocal social influence effects matter.

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 16. 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. Specifically, we find that increasing the of block peers with adjustable rate mortgages by ten percentage points increases the average household's propensity of choosing an adjustable rate by 9.83%.

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 17 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 story. As before, we look at non-occupant households for falsification. In table 18, we find that non-occupant refinance decisions are completely unaffected by the recent refinance decisions of the households living on the same block as the investment property / second or third home.

We provide our final piece of archival data evidence in Table 19. 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 document 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 10^{th} percentile to the 90^{th} 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. These findings contribute to the literature on the role of peer and neighborhood effects in consumption decisions. Importantly, it is worth nothing that we believe these percentages represent the lower bound of the importance of social influence effects. We account only for one's hyperlocal peers in our investigation, though there are undoubtedly other sources of peer influence.

Identifying the influence of peer effects and social influence in household mortgage decision-making has important implications both theoretically and substantively. Theoretically, we apply a new methodology that aids in establishing an issue of first order importance to the fundamental understanding of what drives household decisions. This methodology exploits plausibly exogenous variation in peer decisions across various types of mortgage decisions. Substantively, understanding how social influence can impact household mortgage decisions provides insight into an issue fundamental to consumer welfare. 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[8] owe a combined $10 trillion in mortgage debt.[9] With thousands of lenders[10] 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. 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

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

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

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

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.

	Mean	Std. dev.	Median	N
Panel A: Loan Characteristics				
Refinance (=1)	80.2%	39.9%		548,437
Adjustable Rate Mortgage (=1)	18.4%	38.8%		548,437
Loan Amount	329,485	256,280	291,830	548,437
Loan to Value (if purchase loan)	72.0%	30.7%	80.0%	108,793
Transaction Year 2008 (=1)	22.5%	41.7%		548,437
Transaction Year 2009 (=1)	24.0%	42.7%		548,437
Transaction Year 2010 (=1)	26.8%	44.3%		548,437
Transaction Year 2011 (=1)	26.7%	44.2%		548,437
Panel B: Lender Characteristics				
Bank Lender (=1)	49.7%	50.0%		548,437
Credit Union Lender (=1)	5.9%	23.5%		548,437
Mortgage Company Lender (=1)	22.6%	41.8%		548,437
Wells Fargo Lender (=1)	13.0%	33.6%		548,437
Bank of America Lender (=1)	12.5%	33.0%		548,437
JP Morgan Chase Lender (=1)	5.9%	23.5%		548,437
Panel C: Borrower Characteristics				
Matched to HMDA loan (=1)	58.6%	49.3%		548,437
Distance to Property (miles)	0.36	2.68	0.00	548,211
Co-applicant (=1)	49.8%	50.0%		548,437
Applicant Income (1,000s)	141.26	213.07	101.00	298,179
Race, Asian (=1)	14.0%	34.7%		321,122
Race, Black (=1)	3.9%	19.3%		321,122
Race, White (=1)	60.3%	48.9%		321,122
Ethnicity, Hispanic (=1)	18.4%	38.7%		321,122

Sample: The sample starts with all mortgage loans originated between 2008Q1 and 2011Q4 in Los Angeles. We then follow Bayer Mangum, and Roberts (2016) by dropping observations where the property securing the loan is a condominium or was divided into smaller properties and resold. We also drop if the transaction was flagged as not at arms-length, if the house sold more than once in a single day, or if the sale price was less than $1. To ensure a reasonable panel, we either drop refinances that took place within 3 months of the previous refinance by that owner at that property or combine the information from the two transactions. We further assume that refinances that occurred within 90 days of the purchase loan were more likely to be piggy back loans and are treated as such in the sample. Next, we use an adjusted version of the name scrubbing algorithm used by Bayer, Mangum, and Roberts (2016) to tag those borrowers that are individuals as opposed to trusts or businesses. We also drop any borrowers that concurrently hold four or more properties. This removes professional investors whom this paper is not about. It also removes borrowers with common names giving us confidence that within the sample observations with same-named borrowers are indeed mortgages held by the same borrower. Finally, we drop observations that are missing key information like the location of the property, the name of the buyer, or the lender, or the amount of the loan. It is this sample, and subsamples of this sample, that we will use throughout the paper, except when noted otherwise.

Key Variables: *Refinance* means the loan is a refinance as opposed to a purchase loan. *Adjustable rate mortgages* are defined as those with adjustable or graduated interest rates; all mortgages in the final sample 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 securing the mortgage. *Co-applicant* indicates that there are two people on the mortgage contract. The *income*, *race*, and *ethnicity* variables are from HMDA.

TABLE 2. PROPORTION OF OUTSTANDING LOANS IN THE CENSUS BLOCK THAT HAVE A CERTAIN CHARACTERISTIC.

	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

Sample: Our sample includes approximately 75,000 census blocks and covers 16 time quarters, 2008Q1 – 2011Q4. In panel A, observations are unique at the block-by-quarter level. In panels B, C, and D we look at just one given quarter at a time, such that observations are unique at the block level. To construct the shares, we use all loans made in Los Angeles that meet the criteria described in the Table 1 that were made anytime between 1992Q1-2011Q4. Outstanding mortgage loans originated or most recently refinanced before 1992Q1 are not in the sample, but we assume these loans are a very small proportion of all mortgages still outstanding in the time period we examine in this paper, 2008Q1 – 2011Q4. Note that the sample described in Table 1 is the sample of new mortgages whose characteristics we will be regressing on peer decisions. We extend the sample to 1992Q1 so as to define the rate that mortgage decisions have been made by current neighbors.

Key Variables: *Adjustable Rate Share* is defined as the number of outstanding mortgage loans on the block that have adjustable interest rates divided by the total number of outstanding mortgage loans. *Credit Union Share* is defined as the number of outstanding mortgage loans on the block that were originated by a credit union divided by the total number of outstanding mortgage loans. *Wells Fargo Share* is defined as the number of outstanding mortgage loans on the block that were originated by Wells Fargo divided by the total number of outstanding mortgage loans.

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.

	Average Absolute Value of Difference Between Purchased Household & Block	Average Absolute Value of Difference Between Purchased Household & Adjacent Blocks	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

Sample: The sample consists of every purchase loan in our main sample compared with all outstanding mortgages and properties in the sample. 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 (those houses in the same neighborhood, but *not* on the same 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 adjacent blocks. The fourth column tests whether this difference in differences is statistically different from zero. To be clear, the two groups, block peers and adjacent block peers, are mutually exclusive.

Key Variables: The *year built* is the year that the house was constructed – largely between 1950 and 2010. The *2012 Assessed Value* is the value used to calculate the amount of property tax owed by the household. The average assessed value of a home purchased between 2008 and 2011 is just $358,000.

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. PROPENSITY TO BORROW FROM WELLS FARGO AS A FUNCTION OF THE PEERS BORROWING FROM WELLS FARGO.

	dependent variable: new mortgage is originated by Wells Fargo (=1)				
	(1)	(2)	(3)	(4)	(5)
sample	*owner-occupied refinances*				
Share of all outstanding block loans originated by Wells Fargo	0.177***	0.0415***	0.0412***	0.011	0.0393***
	(17.10)	(3.52)	(3.51)	(0.95)	(3.12)
Share of all outstanding neighborhood loans originated by Wells Fargo		0.557***	0.415***	-0.204***	0.0707*
		(24.040)	(17.510)	(-5.97)	(1.750)
New Loan is an ARM (=1)	-0.0160***	-0.0167***	0.00622***	-0.0210***	0.002
	(-12.15)	(-12.73)	(4.430)	(-15.70)	(1.520)
Co-applicants (=1)	0.0170***	0.0154***	0.0143***	0.0153***	0.0137***
	(14.070)	(12.820)	(11.920)	(12.330)	(10.010)
Quarter Fixed Effects			Y		
Census Group Fixed Effects				Y	
Quarter-by-Group Fixed Effects					Y
N	427,377	427,377	427,377	427,280	410,640

Sample: The sample consists of all the refinance loans from the sample detailed in Table 1 with the further restriction that the mailing address zip code of the borrower and the zip code of the property securing the loan are the same. This further restriction means that the sample used here only includes households who live at or very near the property and are therefore subject to a social influence effect from the households living around the property.

Models: Linear probability models. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

Key Variables: The dependent variable is a dummy equal to 1 if the loan is originated by Wells Fargo, the largest lender in the sample. The *Share of block loans originated by Wells Fargo* is defined as the number of outstanding mortgage loans on the block that were originated by Wells Fargo divided by the total number of outstanding mortgage loans. The *Share of neighborhood loads originated by Wells Fargo* is defined as the number of outstanding mortgage loans in the neighborhood that were originated by Wells Fargo divided by the total number of outstanding mortgage loans in the neighborhood. Note that the block loans are included in the neighborhood loans. There are 16 *Quarter Fixed Effects*, one for each quarter in the sample 2008Q1-2011Q4. The *Census Group Fixed Effects* are meant to soak up even more remaining neighborhood level effects. There are 6363 distinct census block groups in our sample.

Interpretation: In the first model we only include the block share and we find that households behave very similarly to their block peers. But there are likely many non-social influence reasons that this is the case. Including the neighborhood share as a regressor in model (2) soaks up much of the effect. We attribute the significant estimate of neighborhood share (0.557) to the many endogenous reasons that households make similar decisions to households that live near them like availability, advertising, and prices. However, the block share regressor remains significant, suggesting that there are effects from block peer decisions over and above neighborhood peer decisions. This is our key result. Importantly, this effect stays relatively constant when including Quarter and Quarter-by-Group fixed effects. We view model (4) to be mis-specified given the importance of time fixed effects (e.g., mortgage rates and other macroeconomic conditions) in determining mortgage choices. Note that the inclusion of the quarter-by-group fixed effect larger soaks up the effect of the neighborhood share variable suggesting that our research design is working as intended. We adopt specification (3) as our preferred specification given that the inclusion of the very restrictive quarter-by-group fixed effect does not meaningfully change our results. Using the estimates in model (3), we find that increasing the share of block peers with mortgages originated by Wells Fargo by ten percentage points increases the average household's propensity of choosing Wells Fargo by 3.17%. [.41 percentage points increase from a base probability of 13% (from table 1)].

TABLE 5. REFINANCING WITH A LENDER AS A FUNCTION OF THE SHARE OF PEERS BORROWING FROM THAT LENDER

	dependent variable: new mortgage is the same as sample (=1)			
	(1)	(2)	(3)	(4)
sample: refinance loans	*Credit Union*	*Wells Fargo*	*Bank of America*	*JP Morgan Chase*
Share of all outstanding block loans originated by a Credit Union	0.0292**			
	(0.012)			
Share of all outstanding neighborhood loans originated by a Credit Union	0.715***			
	(0.022)			
Share of all outstanding block loans originated by Wells Fargo		0.0412***		
		(0.012)		
Share of all outstanding neighborhood loans originated by Wells Fargo		0.415***		
		(0.024)		
Share of all outstanding block loans originated by Bank of America			0.0255***	
			(0.009)	
Share of all outstanding neighborhood loans originated by Bank of America			0.188***	
			(0.021)	
Share of all outstanding block loans originated by JP Morgan Chase				0.0231
				(0.015)
Share of all outstanding neighborhood loans originated by JP Morgan Chase				-0.211***
				(0.038)
New Loan is an ARM (=1)	0.0472***	0.00622***	0.111***	-0.0325***
	(0.001)	(0.001)	(0.002)	(0.001)
Co-applicants (=1)	0.0177***	0.0143***	0.00907***	0.00377***
	(0.001)	(0.001)	(0.001)	(0.001)
Quarter Fixed Effects	Y	Y	Y	Y
N	427,377	427,377	427,377	427,377

Sample: The sample consists of all the refinance loans from the sample detailed in Table 1 with the further restriction that the mailing address zip code of the borrower and the zip code of the property securing the loan are the same.

Models: Linear probability models. Each model is identical to model (3) from the previous table. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

Key Variables: The share variables are defined as in the previous table for the respective lender of interest.

Interpretation: In this table we reach the same conclusion for Credit Unions and Bank of America as we did for Wells Fargo. In model (4) we find a similar magnitude for JP Morgan Chase, but the estimate is not significant at standard levels. In model (1), we estimate that increasing the share of block peers with mortgages originated by credit unions by ten percentage points increases the average household's propensity of borrowing from a credit union by 4.95%. [.29 percentage points increase from a base probability of 5.9% (from table 1)]. In model (3), we estimate that increasing the share of block peers with mortgages originated by Bank of America by ten percentage points increases the average household's propensity of borrowing from Bank of America by 2.04%. [.255 percentage points increase from a base probability of 12.5% (from table 1)].

TABLE 6. BORROWING A PURCHASE LOAN FROM A LENDER AS A FUNCTION OF THE PEERS BORROWING FROM THAT LENDER

	dependent variable: new mortgage is the same as sample (=1)			
	(1)	(2)	(3)	(4)
sample: purchase loans	*Credit Union*	*Wells Fargo*	*Bank of America*	*JP Morgan Chase*
Share of all outstanding block loans originated by a Credit Union	0.01			
	(0.010)			
Share of all outstanding neighborhood loans originated by a Credit Union	0.282***			
	(0.021)			
Share of all outstanding block loans originated by Wells Fargo		-0.0136		
		(0.017)		
Share of all outstanding neighborhood loans originated by Wells Fargo		0.444***		
		(0.035)		
Share of all outstanding block loans originated by Bank of America			0.019	
			(0.015)	
Share of all outstanding neighborhood loans originated by Bank of America			0.226***	
			(0.032)	
Share of all outstanding block loans originated by JP Morgan Chase				-0.00924
				(0.016)
Share of all outstanding neighborhood loans originated by JP Morgan Chase				0.164***
				(0.048)
New Loan is an ARM (=1)	0.0186***	0.00921***	-0.0232***	0.000732
	(0.002)	(0.003)	(0.003)	(0.002)
Co-applicants (=1)	0.00748***	0.0160***	0.0140***	0.00217**
	(0.001)	(0.002)	(0.002)	(0.001)
Quarter Fixed Effects	Y	Y	Y	Y
N	108,541	108,541	108,541	108,541

Sample: The sample consists of all the purchase loans from the sample detailed in Table 1.

Models: Linear probability models. The models are the same as in the previous table. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

Key Variables: The share variables are defined as in the previous table for the respective lender of interest.

Interpretation: In the previous table we concluded that households, when making refinance decisions, are affected by their neighbors. Households making purchase loans, on the other hand, have never lived there and so should not be affected by any social influences from these new neighbors. We find that, indeed, 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. Note that, as before, a household does behave similarly to the larger area to which its moving. This is because of a number of neighborhood-level effects that influence lender choice including, for example, availability, advertising, and prices.

TABLE 7. 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.

	dependent variable: borrower pair has common lender (=1)
	(1)
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

Sample: The sample is all Los Angeles refinance mortgages outstanding on January 1, 2011 that were originated between 2009Q1 – 2010Q4, the two years before our cross section of interest. All properties in census blocks with fewer than five households are excluded. We then create all pairs of outstanding refinance loans between households who live in the same neighborhood.

Models: Linear probability models. We estimate the effect of living in the same block on having a mortgage loan from the same lender. 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 tract level, respectively.

Key Variables: Households that 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. Because it is possible for two households to be in the same neighborhood, but not the same block, we use Census Tracts as our geographic fixed effect level. These are the next largest census delineations after block groups and correspond roughly to zip codes.

Interpretation: A pair of households is 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. Two households living in the same neighborhood share the same lender 3.81% of the time. Living on the same block increases this by .000884 percentage points or 1.02%.

TABLE 8. CHOOSING AN ARM WHEN REFINANCING AS A FUNCTION OF THE SHARE OF PEERS WITH ARMS.

	dependent variable: new mortgage is an ARM (=1)				
	(1)	(2)	(3)	(4)	(5)
sample			*owner-occupied refinances*		
Share of all outstanding block loans with adjustable rates	0.277***	0.0275***	0.0273***	0.0160**	0.0194***
	(45.04)	(3.94)	(3.99)	(2.39)	(2.65)
Share of all outstanding neighborhood loans with adjustable rates		0.796***	0.577***	0.965***	0.0588**
		(56.840)	(37.660)	(56.000)	(2.420)
Bank Lender	0.196***	0.189***	0.168***	0.186***	0.163***
	(125.380)	(122.290)	(107.980)	(117.070)	(88.060)
Credit Union Lender	0.242***	0.237***	0.215***	0.242***	0.215***
	(76.660)	(75.490)	(68.770)	(75.900)	(61.050)
Mortgage Company Lender	0.0307***	0.0252***	0.0226***	0.0234***	0.0195***
	(19.590)	(15.990)	(13.960)	(14.390)	(10.010)
Outstanding Loan is an ARM (=1)	0.102***	0.0923***	0.0667***	0.0853***	0.0611***
	(63.670)	(58.690)	(42.750)	(54.400)	(35.090)
Co-applicants (=1)	-0.0109***	-0.00996***	-0.00278**	-0.00882***	-0.00216
	(-7.87)	(-7.24)	(-2.08)	(-6.25)	(-1.40)
Quarter Fixed Effects			Y		
Census Group Fixed Effects				Y	
Quarter-by-Group Fixed Effects					Y
N	338,042	338,042	338,042	337,905	319,507

Sample: The sample consists of all the refinance loans from the sample detailed in Table 1 with the further restriction that the mailing address zip code of the borrower and the zip code of the property securing the loan are the same. This further restriction means that the sample used here only includes households who live at or very near the property and are therefore subject to a social influence effect from the households living around the property.

Models: Linear probability models. The dependent variable is a dummy equal to 1 if the loan is an ARM. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

Key Variables: The *Share of all outstanding block loans with adjustable rates* is defined as the number of outstanding mortgage loans on the block that have adjustable rates divided by the total number of outstanding mortgage loans. The *Share of all outstanding neighborhood loans with adjustable rates* is defined as the number of outstanding mortgage loans in the neighborhood with adjustable interest rates divided by the total number of outstanding mortgage loans in the neighborhood. Note that the block loans are included in the neighborhood loans.

Interpretation: In this and the following tests we explore the hypothesis that households are more likely to choose adjustable rate mortgages if their neighbors have adjustable rate mortgages. We include two key variables: neighborhood share as a control and block share as the variable of interest. As discussed at length in Table 4, we include progressively more restrictive fixed effects and find a consistent effect coming from block peers in models (2) - (5). This effect is a peer effect over and above neighborhood share effects and is consistent with a social influence that operates at hyper local levels. Using our preferred specification, (3), we find that increasing the share of block peers with adjustable rate mortgages by ten percentage points increases the average household's propensity of choosing an adjustable rate by 1.48%. [.27 percentage points increase from a base probability of 18.4% (from table 1)].

TABLE 9. CHOOSING AN ARM AS A FUNCTION OF THE SHARE OF PEERS WITH ARMS.

	dependent variable: new mortgage is an ARM (=1)			
	(1)	(2)	(3)	(4)
sample	*owner-occupied refinances*		*purchase loans*	
Share of all outstanding block loans with adjustable rates	0.0273***	0.0221***	0.00734	0.0145
	(3.99)	(2.79)	(0.84)	(1.30)
Share of all outstanding neighborhood loans with adjustable rates	0.577***	0.481***	0.575***	0.604***
	(37.660)	(25.800)	(29.630)	(21.990)
Bank Lender	0.168***	0.107***	0.117***	0.0663***
	(107.980)	(58.180)	(54.200)	(23.870)
Credit Union Lender	0.215***	0.0628***	0.119***	0.0814***
	(68.770)	(19.610)	(15.080)	(8.710)
Mortgage Company Lender	0.0226***	0.0205***	0.0380***	0.0213***
	(13.960)	(10.910)	(23.310)	(8.370)
Outstanding Loan is an ARM (=1)	0.0667***	0.0694***		
	(42.750)	(37.180)		
Co-applicants (=1)	-0.00278**	-0.00599***	0.00208	-0.0105***
	(-2.08)	(-3.63)	(1.170)	(-4.30)
Quarter Fixed Effects	Y	Y	Y	Y
Income Quartile Controls		Y		Y
Race and Ethnicity Controls		Y		Y
N	338,042	185,652	108,541	62,348

Sample: In models (1) and (2), the sample consists of all refinance loans from the sample detailed in Table 1 with the further restriction that the mailing address zip code of the borrower and the zip code of the property securing the loan are the same. In models (3) and (4), the sample is all purchase loans detailed in Table 1.

Models: Linear probability models. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level. Model (1) is identical to model (3) in the previous table.

Key Variables: New to this table are the income quartile controls, there are 4, and race and ethnicity controls. These variables are defined in table 1. The sample falls dramatically as we are only able to confidently match approximately half of the loans in the CoreLogic sample to HMDA.

Interpretation: This table provides two key insights. The first is that, in model (2), the inclusion of more household level controls does not qualitatively change our results. The second is that, as before, households taking our purchase loans, who have therefore not been lived there and been exposed to their neighbors, are not affected by any 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. This result is consistent with a social influence effect that operates at local level. Note that, as before, households taking out purchase loans do behave similarly to other borrowers in the neighborhood. This is because of a number of larger area-level effects that influence ARM choice including, for example, availability, advertising, and prices.

TABLE 10. CHOOSING AN ARM, COMPARING NON-OCCUPANT OWNERS AND OCCUPANT OWNERS.

	dependent variable: new mortgage is an ARM (=1)			
	(1)	(2)	(3)	(4)
sample	*refinances by non-occupant owners*		*refinances by occupant owners*	
Share of all outstanding block loans with adjustable rates	0.00548	-0.0862*	0.0273***	0.0221***
	(0.14)	(-1.95)	(3.99)	(2.79)
Share of all outstanding neighborhood loans with adjustable rates	0.122	0.383***	0.577***	0.481***
	(1.520)	(4.010)	(37.660)	(25.800)
Bank Lender	0.173***	0.0341**	0.168***	0.107***
	(19.420)	(2.460)	(107.980)	(58.180)
Credit Union Lender	0.184***	-0.00138	0.215***	0.0628***
	(4.440)	(-0.04)	(68.770)	(19.610)
Mortgage Company Lender	0.0629***	0.0143	0.0226***	0.0205***
	(5.720)	(0.880)	(13.960)	(10.910)
Outstanding Loan is an ARM (=1)	0.103***	0.0858***	0.0667***	0.0694***
	(9.480)	(6.320)	(42.750)	(37.180)
Co-applicants (=1)	-0.0191**	-0.0128	-0.00278**	-0.00599***
	(-2.16)	(-1.27)	(-2.08)	(-3.63)
Quarter Fixed Effects	Y	Y	Y	Y
Income Quartile Controls		Y		Y
Race and Ethnicity Controls		Y		Y
N	6,699	3,311	338,042	185,652

Sample: In models (1) and (2), the sample consists of all refinance loans from the sample detailed in Table 1 with the further restriction that the mailing address zip code of the borrower and the zip code of the property securing the loan are *not* the same. In models (3) and (4), we require that the two zip codes be the same. In this way we compare households that do not occupy the property with those that do.

Models: Linear probability models. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

Interpretation: We find that households refinancing mortgage loans secured by properties they do not occupy, i.e., second or third homes or investment properties, are not significantly 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 11. CHOOSING AN ARM, ARE NON-OCCUPANT OWNERS AFFECTED BY THEIR ACTUAL NEIGHBORS?

	dependent variable: new mortgage is an ARM (=1)			
	(1)	(2)	(3)	(4)
sample	*refinances by non-occupant owners*			
Share of all outstanding block loans on owner's block with adjustable rates	0.115***	0.0720+	0.115***	0.0719+
	(2.78)	(1.53)	(2.78)	(1.53)
Share of all outstanding neighborhood loans in owner's group with adjustable rates	0.0455	0.298***	0.0398	0.260***
	(0.550)	(3.290)	(0.470)	(2.900)
Share of all outstanding block loans on property's block with adjustable rates			0.00334	-0.0899**
			(0.090)	(-2.04)
Share of all outstanding neighborhood loans in property's neighborhood with adjustable rates			0.094	0.317***
			(1.150)	(3.350)
Bank Lender	0.175***	0.0357***	0.174***	0.0352**
	(19.750)	(2.590)	(19.560)	(2.540)
Credit Union Lender	0.197***	0.00115	0.187***	-0.000487
	(4.730)	(0.030)	(4.530)	(-0.01)
Mortgage Company Lender	0.0655***	0.0146	0.0650***	0.0151
	(5.960)	(0.900)	(5.900)	(0.930)
Outstanding Loan is an ARM (=1)	0.104***	0.0844***	0.102***	0.0849***
	(9.560)	(6.250)	(9.350)	(6.260)
Co-applicants (=1)	-0.0198**	-0.0134	-0.0189**	-0.0117
	(-2.25)	(-1.33)	(-2.14)	(-1.16)
Quarter Fixed Effects	Y	Y	Y	Y
Income Quartile Controls		Y		Y
Race and Ethnicity Controls		Y		Y
N	6,734	3,314	6,694	3,308

Sample: The sample consists of all refinance loans from the sample detailed in Table 1 with the further restriction that the mailing address zip code of the borrower and the zip code of the property securing the loan are not the same.

Model: Linear probability models. Coefficients significant at the 15%, 10%, 5%, and 1% levels are marked with a +, *, **, and ***, respectively. Standard errors are clustered at the census block level.

Key Variables: The *Share of block loans around the owner's block* looks at the block of the non-occupant owner's primary residence. This captures the share of mortgages held by his hyperlocal peers that are ARMs.

Interpretation: In the previous table, we find that households who are refinancing a mortgage loans on secured by properties they do not occupy, i.e., second homes or investment properties, are not significantly affected by a hyper local social influence from the people that live immediately around the property. In this table we ask if these non-occupant owners behave like the households that live around their primary residence, where they *do* actually live. We find that households do behave like their neighbors, even when making decisions about mortgages on properties not in the neighborhood. This result is weakened somewhat by the inclusion of the demographic controls, but we attribute some of this to the size of the sample. In models (3) and (4), we include the shares of ARMs in the area around the property, as well as the area around the primary residence. Our results are unchanged. Households behave like their hyperlocal peers, even when making decisions on properties not near those peers.

TABLE 12. TESTING FOR SOCIAL INFLUENCE IN BORROWERS WHO MOVE TO A NEW PROPERTY.

	dependent variable: new mortgage is an ARM (=1)		
	(1)	(2)	(3)
sample	*purchase loans with different site and mailing zip codes*	*refinances by borrowers who continued to have different zips*	*refinances by those who used the same zip code for the refinance*
Share of all outstanding block loans with adjustable rates	0.0178	0.00989	0.0356*
	(0.75)	(0.23)	(1.92)
Share of all outstanding neighborhood loans with adjustable rates	0.752***	0.519***	0.477***
	(17.770)	(6.710)	(13.750)
Bank Lender	0.245***	0.363***	0.305***
	(32.110)	(26.680)	(52.240)
Credit Union Lender	0.0872***	0.278***	0.196***
	(3.010)	(7.390)	(13.780)
Mortgage Company Lender	0.102***	0.108***	0.0757***
	(15.230)	(7.570)	(11.470)
Outstanding Loan is an ARM (=1)		0.160***	0.127***
		(14.060)	(26.590)
Co-applicants (=1)	-0.0556***	-0.0194*	-0.0243***
	(-9.84)	(-1.90)	(-5.60)
Quarter Fixed Effects	Y	Y	Y
N	25,978	7,799	42,266

Sample: This sample consists of all borrowers who made purchase loans sometime between 2002Q1 and 2011Q4 and then later refinanced that purchase loan. The longer time period is necessary to do this test because the sample of households that moved in and refinanced between 2008Q1 and 2011Q4 is too small. All those loans being refinanced in models (2) and (3) are refinanced purchase loans used to estimate (1). I.e., the average purchase loan (of which there are 25,978) made in this sample is refinanced approximately 2 times (7,799 + 42,266).

Models: Linear probability models. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the census block level.

Interpretation: As before, we find that households taking out purchase loans are not affected by the choices of households who live near the property. They have not lived near them before and are therefore not socially influenced by them. In this case we require that the mailing zip and site zip of the purchase loan borrower are different. We then follow the households that later refinance – some of whom were investors and remained non-occupants (model 2), but many others of whom did move to the property (model 3). We find that those did not move were not affected by the people living around the property but those who did move, and were therefore more likely to interact with these new neighbors, were socially influenced. This result also demonstrates that our previous results were not simply picking up some differences between purchase loans and refinance loans or the types of people that refinance as compared to the types of people that do not (and therefore only appear in the purchase sample).

TABLE 13. OUTSTANDING LOANS AND REFINANCE RATES OVER TIME

	Number of Outstanding Loans…	…Percent of which Refinanced
2008 Q1	1,396,845	2.84%
2008 Q2	1,397,761	2.51%
2008 Q3	1,398,366	1.38%
2008 Q4	1,399,142	1.01%
2009 Q1	1,399,824	1.80%
2009 Q2	1,400,514	2.35%
2009 Q3	1,401,376	1.88%
2009 Q4	1,402,941	1.80%
2010 Q1	1,403,754	1.53%
2010 Q2	1,405,051	1.51%
2010 Q3	1,406,611	2.47%
2010 Q4	1,408,636	3.10%
2011 Q1	1,409,714	2.11%
2011 Q2	1,411,193	1.54%
2011 Q3	1,412,640	2.18%
2011 Q4	1,414,764	2.88%

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

TABLE 14. CHARACTERISTICS OF THE REFINANCE HOUSEHOLDS

	Mean	Std. dev.	Median	N
Panel A: 2008Q1				
Refinance (=1)	2.8%			1,396,845
Outstanding Loan is an ARM (=1)	43.9%			747,935
Outstanding Loan is a Refinance (=1)	80%			1,383,939
Quarters Since Last Refinance/Purchase	17.49	17.55	11.00	1,383,939
Co-applicant (=1)	47.6%			1,396,845
Applicant Income (1,000s)	125.39	169.44	95.00	620,228
Distance to Property (miles)	6.90	103.07	0.00	44,096
Race, White (=1)	50.6%			676,405
Panel B: 2009Q4				
Refinance (=1)	1.8%			1,402,941
Outstanding Loan is an ARM (=1)	43.8%			750,791
Outstanding Loan is a Refinance (=1)	80%			1,388,308
Quarters Since Last Refinance/Purchase	22.02	18.39	16.00	1,388,308
Co-applicant (=1)	47.2%			1,402,941
Applicant Income (1,000s)	125.49	174.84	94.00	646,540
Distance to Property (miles)	7.96	113.47	0.00	33,972
Race, White (=1)	51.8%			699,940
Panel A: 2011Q4				
Refinance (=1)	2.9%			1,414,764
Outstanding Loan is an ARM (=1)	41.3%			758,484
Outstanding Loan is a Refinance (=1)	79%			1,398,463
Quarters Since Last Refinance/Purchase	26.30	20.23	22.00	1,398,463
Co-applicant (=1)	46.8%			1,414,764
Applicant Income (1,000s)	125.41	174.05	94.00	683,375
Distance to Property (miles)	8.55	117.52	0.00	48,689
Race, White (=1)	53.5%			734,977

Sample: The sample is all households with outstanding loans owned by people (as opposed to trusts or businesses) who own no more than three properties. Loans originated before 1992 are not included in the sample as data collection efforts had not yet begun. Each panel looks at a different cross section of all outstanding loans as of the first day of that quarter. Some of the older loans are missing the interest rate type variable which means we cannot determine if the outstanding loan is an adjustable or fixed rate mortgage. Approximately half of the loans do not have HMDA matches and so demographic variables are missing.

Key Variables: *Refinance* is a dummy equal to one if the outstanding loan was refinanced that quarter. *Quarters since last Refinance/Purchase* is the number of quarters since the outstanding loan was originated. *Distance to Property* is the distance between the address of the owner of the property and the property conditional on a refinance occurring that quarter.

TABLE 15: PROPORTION OF LOANS REFINANCED DURING THE PREVIOUS 3 MONTHS, 6 MONTHS, OR 12 MONTHS.

	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%

Sample: The underlying sample is that described in the tables 13 and 14. In this sample, observations are unique at the block-by-quarter level

Key Variables: *Proportion of Block Loans Refinanced During the Last 2 Quarters* is defined as the number of refinances in the previous 2 quarters by households in the sample divided by the number of outstanding mortgage loans at households in the sample. In the following regressions this share is adjusted to exclude the household's own loan.

Interpretation: There is a significant variation across neighborhoods in the proportion of households that have recently refinanced.

TABLE 16: HOUSEHOLD PROPENSITY TO REFINANCE THEIR MORTGAGE IF THEIR NEIGHBORS RECENTLY HAVE

	dependent variable: household refinanced this quarter (=1)				
	(1)	(2)	(3)	(4)	(5)
sample			*all households*		
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

Sample: The sample is that described in Tables 13 and 14.

Models: Linear probability models. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the household level.

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. As before, we adopt model (3) as our preferred specification. We find that increasing the of block peers with adjustable rate mortgages by ten percentage points increases the average household's propensity of choosing an adjustable rate by 9.83%. [.285 percentage points increase from a base probability of 2.9% (from table 1)].

TABLE 17: HOUSEHOLD PROPENSITY TO REFINANCE, INCLUDING LENDER FIXED EFFECTS

	dependent variable: household refinanced this quarter (=1)			
	(1)	(2)	(3)	(4)
sample	*all households*			
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

Sample: The sample is that described in Tables 13 and 14.

Models: Linear probability models. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the household level.

Key Variables: In models (3) and (4) we include 18 *Originator of Outstanding Loan Fixed Effects* for the 18 lenders in our sample with more than 50,000 mortgage originations.

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. This result allows us to rule out a lender fixed effect story wherein households make similar decisions to their neighbors only because they share the same lender. If anything, the social influence effect becomes stronger after including the specific lender fixed effect.

TABLE 18: HOUSEHOLD REFINANCE, FALSIFICATION TEST USING NON-OCCUPANT HOUSEHOLDS

	dependent variable: household refinanced this quarter (=1)				
	(1)	(2)	(3)	(4)	(5)
sample	*non-occupant owned households*				
Share of all block loans that have refinanced in the last 2 quarters	0.0359***	0.00632	0.00656	0.00000326	0.00181
	(5.94)	(0.92)	(0.96)	(0.00)	(0.22)
Share of all neighborhood loans that have refinanced in the last 2 quarters		0.109***	0.0954***	0.120***	0.0233
		(7.870)	(6.530)	(7.200)	(0.900)
Outstanding Loan in an ARM	-0.00547***	-0.00540***	-0.00558***	-0.00538***	-0.00542***
	(-8.20)	(-8.09)	(-8.35)	(-6.53)	(-6.98)
Outstanding Loan is a Refinance	-0.657***	-0.657***	-0.656***	-0.702***	-0.648***
	(-20.14)	(-20.14)	(-20.16)	(-27.67)	(-20.00)
Co-applicants (=1)	0.00188***	0.00172***	0.00184***	0.00167**	0.00196***
	(3.290)	(3.020)	(3.250)	(2.330)	(2.760)
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	326,544	326,544	326,544	326,501	306,528

Sample: The sample is that described in Tables 13 and 14, except with the added restriction that the mailing address zip code on the outstanding loan and the refinance loan are not the same as the property's zip code. In this way, we can look at the sample of households that are not owner occupied.

Models: Linear probability models. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively. Standard errors are clustered at the household level.

Interpretation: A household that does not live at the property is not at all affected by the decisions of the households that live around the property. This result provides further evidence for a social influence effect operating at a hyper local l

TABLE 19: HOUSEHOLD REFINANCE, FALSIFICATION TEST USING OUTSTANDING LOAN MATCHING

	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

Sample: 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.

Models: These specifications are identical to those in model (3) from the previous tables.

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.