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Household Mortgage Refinancing Decisions Are Neighbor Influenced

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Abstract

Can social influence effects help explain regional heterogeneity in refinancing activity? Neighborhood social influence effects have been shown to affect publicly observable decisions, but their role in private decisions, like refinancing, remains unclear. Using precisely geolocated data and a nearest-neighbor research design, we find that households are 7% more likely to refinance if a neighbor within 50 meters has recently refinanced. Consistent with a word-of-mouth mechanism, social influence effects are weaker when neighbors are farther away and non-existent for non-occupants. Our results illustrate the importance of the proximate community for household wealth accumulation and the transmission of monetary policy.

JEL Classification: D12, D14, D71, H31, R23
Keywords: Household Finance, Refinancing, Peer Effects, Neighborhoods

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1 Introduction

Mortgage refinancing is important for households' wealth and for the transmission of monetary policy to household consumption (Di Maggio et al., 2020; Keys et al., 2016; Wong, 2019). Recent empirical evidence has documented significant regional heterogeneity in refinancing activity that leaves some households and local economies better off (Beraja et al., 2019). While there is much theoretical and practical interest in identifying the mechanisms underlying spatial clustering in economic decisions, the existing empirical evidence on neighborhood-level influence effects has focused predominantly on choices that are conspicuous and publicly observable.[1] These settings make it difficult to disentangle the role of visual salience from other channels such as word-of-mouth exchanges. This distinction is crucial for decisions such as refinancing, which are relatively private, inconspicuous choices. In this paper, we investigate the importance of word-of-mouth social interactions for explaining regional heterogeneity in refinancing.

This paper's contributions are twofold. First, we identify the importance of hyperlocal social networks in driving regional refinancing activity and document how local these effects can be. To overcome many of the challenges that preclude the identification of neighbor peer effects, we take a nearest-neighbor research design to millions of precisely geolocated refinance decisions. Specifically, we investigate the impact of a household's immediate neighbors (those who live within 50 meters) while, in our first strategy, including a local geography fixed effect, and, in our second strategy, controlling for the refinancing decisions of neighbors slightly farther away (those within 100 meters or 250 meters). The identifying assumption is that while households may choose to live in particular neighborhoods, they are less likely to choose, or be able to choose, specific parcels. This design has been used extensively in the recent empirical literature on neighborhoods to identify spatial spillover effects of, for example, foreclosure, criminal activity, and health risks.[2] We further validate the identifying assumption in our setting by conducting a survey of real estate agents. Over 90%, of respondents reported that prospective homeowners rarely search for hyperlocal geographies, but rather identify a neighborhood or set of neighborhoods where they want to live and then choose

[1] For example, extant work documents neighbor effects in car buying (Grinblatt et al., 2008; McShane et al., 2012), the purchase of investment properties (Bayer et al., 2021), exterior home improvements (Bollinger and Gillingham, 2012; Newman and Staelin, 1972), and foreclosure (Anenberg and Kung, 2014; Campbell et al., 2011; Gupta, 2019; Kalda, 2019; Towe and Lawley, 2013). A notable exception is Bayer et al. (2008) who find evidence that neighbors share job referrals.

[2] See, for example, Anenberg and Kung (2014); Bayer et al. (2021, 2008); Campbell et al. (2011); Currie et al. (2015); Linden and Rockoff (2008); Towe and Lawley (2013).

from among the homes currently for sale.[3] We document that household refinancing decisions are strongly correlated with the decisions of their immediate neighbors. Specifically, the average owner-occupied household in Los Angeles County is 7% more likely to refinance if an immediate neighbor refinanced in the previous quarter. This significant correlation exists even after controlling for a rich set of property-specific, borrower-specific, and outstanding loan-specific control variables and including very fine geography and time fixed effects.

Second, we provide compelling evidence consistent with word-of-mouth exchanges being the mechanism through which households are affected by their neighbors. Since neighbors' refinances are not publicly observable, the existence of hyperlocal spatial clustering in refinance activity is most consistent with a word-of-mouth transmission channel. To provide more evidence in support of this channel, we investigate two settings where we can plausibly vary the intensity of word-of-mouth social interactions.

We first investigate how estimated neighbor effect changes as the distance between the household and the neighbors increases. If hyperlocal clustering in refinancing operates primarily through word-of-mouth social interactions, then we would expect to find that the strength of hyperlocal influence is strongest among immediate neighbors and decays as the geographical distance between them increases. To test whether this is the case, we investigate the strength of hyperlocal influence effects from neighbors who are less than 50 meters away, between 50 and 100 meters away, and between 100 and 250 meters away. We find that a household's immediate neighbors exert a social influence effect nearly twice as strong as that from neighbors between 50 and 100 meters away and more than three times as strong as that from neighbors who are between 100 and 250 meters away. Along with being consistent with word-of-mouth social interactions, this result allows us to both further document the importance of hyperlocal neighbors and quantify the extent to which their effects spatially decay.

In our second test for the evidence of word-of-mouth interactions, we focus on non-occupant owners. These owners are a natural falsification group since they are unlikely to socially interact with their neighbors. Intuitively, this test provides a sharp contrast between two potential mechanisms. If correlations in refinancing activity between households and their neighbors were spurious and there was no causal peer effect – for example, if sorting and correlated shocks were behind the hyperlocal clustering in refinance activity – then we would expect to see a positive correlation for both

[3] We describe the interviews in Online Appendix A.

non-owner-occupied and owner-occupied households. Alternatively, if social interactions were behind the hyperlocal influence effects, then we would expect the refinance decisions of non-occupant owners, since they are less likely to socially interact with surrounding households, to be uncorrelated with the immediate neighbors. We find that non-occupied households' refinance decisions are indeed uncorrelated with their immediate neighbors' refinance decisions. Furthermore, limiting the sample to owners whose primary residences are in our sample and including an owner-by-quarter fixed effect, we again find that households' refinance decisions are especially correlated with their immediate neighbors' refinance decisions. Importantly, these homeowners with multiple properties *are* socially influenced by the neighbors at their primary residences, with whom they are presumably more likely to interact. Taken together, our findings are most consistent with a hyperlocal neighbor effect operating via a word-of-mouth channel.

Back-of-the-envelope calculations estimate that social influence effects from hyperlocal neighbors explain nearly 1.5% of all mortgage refinancing and save U.S. households over $175 million every quarter. Furthermore, there are at least three reasons the economically important effects that we document here underestimate the true magnitude of the neighborhood social influence effect. First, our research design identifies the effect of immediate neighbors by controlling for the decisions of those slightly farther away. If these slightly more distant neighbors *also* influence refinancing decisions, then our estimates, which do not capture this effect, will, by construction, understate the full effect of neighbors' social influences. Second, our estimate is also mechanically biased toward zero since we implicitly assume all households are "treated" with neighbor interactions. If a household only interacts with some, but not all, of their nearest neighbors, then what we estimate is really the treatment-on-the-treated effect, which will be less than the true social influence effect. This is especially important in private decisions because, unlike in public decisions in which everybody is likely to observe the neighbor's new car or foreclosure, the average household probably does not talk with every one of their neighbors. Finally, at a broader level, our work focuses exclusively on isolating and quantifying the causal effects of social interactions from one part of the household's social network: their neighborhood peers. By isolating the effect of one peer group, and ignoring other peer groups like friends (Bailey et al., 2018) and co-workers (Maturana and Nickerson, 2019), our estimate understates the importance of social influence, more broadly, for households' refinance decisions.

To these important papers that, like this one, investigate the effects of peers on households' refinance and mortgage decisions, our work makes two contributions. First, we investigate a different part of the household's social network: their neighbors. Given the interest in understanding the drivers of regional variation in refinancing activity and its importance for local housing markets, identifying and quantifying the influence of this group is of first order importance (Beraja et al., 2019; Glaeser et al., 2014; Wong, 2019). Our result not only illustrates the importance of neighbors as part of the social network, but, since refinancing generally benefits households, we are also able to push against the largely negative effects of neighbors that much of the literature suggests, especially when documenting "Keeping up with the Jones" effects (Agarwal et al., 2020; Mitton et al., 2018). Understanding the effects of neighbors, both positive and negative, will be increasingly important given social trends. The popularization of neighborhood-based apps such as Nextdoor and the shift to working from home, two trends amplified by the recent COVID-19 pandemic, mean that households and their neighbors will be increasingly connected (BLS, 2017; Brynjolfsson et al., 2020). The second contribution we make to this literature is evidence not just of a positive social influence effect, but also, only possible because of the richness of our data, a quantification of how the influence decays over distance.

Our finding that households' nearest neighbors socially influence refinance decisions also contributes to the larger literature that seeks to understand why households refinance or, more pertinently, fail to do so even when optimal (see, especially, Agarwal et al. (2016); Johnson et al. (2019); and Gomes et al. (2020) for a review of the literature). Indeed, estimates from November 2020 suggest that there are millions of homeowners who could save hundreds of dollars each month by refinancing.[4] Our findings suggest that policymakers and local community leaders may do well to use behavioral interventions that utilize hyperlocal targeting strategies and encourage social interactions.

2 Identification Strategy

Two well-known endogeneity issues confound the identification of neighborhood peer effects: endogenous group formation and correlated unobservables (Brock and Durlauf, 2001; Manski, 1993, 2000;

[4] See https://www.blackknightinc.com/blog-posts/refi-incentive-hits-all-time-high-19-4m-candidates-6b-in-monthly-savings-available/, accessed January 30, 2021.

Moffitt, 2001; Soetevent, 2006). First, households choose where to live partly based on similarities with those they will be living near. Since households in similar stages of life and with similar incomes will make similar refinancing decisions, there will likely be correlations between the decisions made by households and the decisions made by their neighbors. Second, households living nearby are likely to use the same financial institutions and face the same market conditions. Shared exposure to often unobservable local shocks may drive households to make the same decisions. Finally, if households are not only influenced by their neighbors but also influence them, then neighborhood peer effects may be difficult to detect.

To overcome these challenges, we use a nearest-neighbor research design that models households' refinancing decisions as a function of their very nearest neighbors' decisions while controlling for the decisions made by neighbors who live slightly farther away. In our preferred specification, the nearest neighbors are those households living within 50 meters, and the neighborhood is the census block group. Defined this way, our sample's average household has 11 nearest neighbors and lives in one of Los Angeles's 6,213 neighborhoods (each inhabited by an average of 246 households). The strategy assumes that *within* a neighborhood, a household's *nearest* neighbors are randomly assigned. If a household's nearest neighbors are conditionally random, then endogenous group formation and correlated unobservables no longer bias estimates of the social influence effect from these nearest neighbors.

We can therefore identify social influence effects using the following linear probability model:

$$Refi_{it} = \alpha + \beta_1 \times Nbr\ Refis_{i,t-1} + \delta \times X_i + \kappa_{lt} + \phi_{gt} + \epsilon_{it}, \tag{1}$$

where $Refi_{it}$ is binary variable equal to 100 if household i refinanced in quarter t. Our parameter of interest, β_1, estimates the effect of $Nbr\ Refis_{i,t-1}$, the count of hyperlocal neighbors who refinanced in the last quarter, on the household's likelihood of refinancing this quarter. X_i is a vector of variables that control for characteristics of the borrowers, their property, and their outstanding mortgage. A lender by quarter fixed effect, denoted κ_{lt}, controls for variation in the likelihood of lenders encouraging their borrowers to refinance at particular points of time. Finally, we include a census block group by quarter fixed effect, ϕ_{gt}, to absorb the effects of sorting and common shocks. Since hyperlocal neighbors are *included* in the block group, β_1 picks up the outsized effect of hyperlocal neighbors.

3 Data Description

We create a panel data set that follows households in Los Angeles County from 2008 to 2012. In this section, we describe the data sources, define neighbor activity, and summarize our final sample.

3.1 Data Sources

Our primary data set uses data from two public sources: deeds registries and tax assessors' offices. These data are cleaned and standardized by the real estate data company, DataQuick Information Services (now CoreLogic Solutions). The deeds registries detail mortgage loans, recording the names of the borrowers (and, in the case of purchase loans, the sellers), the date of the origination, the purpose of the loan (purchase or refinance), the loan amount, whether the interest rate on the loan is fixed or adjustable, and the name of the lender. Local tax assessors' offices record ownership and property characteristics, e.g., square feet, year built, appraised value, and, crucially, the exact latitude and longitude, of every property in the county.

We supplement the Dataquick data with Home Mortgage Disclosure Act (HMDA) data. HMDA is a mortgage level database listing all mortgage applications, both approved and denied, made to qualifying lending institutions. We successfully merge HMDA data into our main data set using loan purpose (purchase or refinance), loan amount, presence of a co-signer, census tract, lender name, and year of application for 37% of our sample.[5] For this subsample, we observe the homeowner's race, sex, and income since HMDA includes these variables.[6]

We focus on one county to ensure that recorded transactions use consistent coding rules. We choose Los Angeles for three reasons. First, Los Angeles has a long panel of reliable, non-missing data, giving us a complete picture of every households' mortgage decisions between 1992 and 2012. Second, with over 10 million inhabitants, the population of Los Angeles County alone exceeds that of 41 individual states. And third, not only large in terms of population, Los Angeles also has the world's third-largest metropolitan economy and a nominal GDP of $700 billion, making it an important economic center.

[5] 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.

[6] Since our deeds records include only approved loans, none of the denied loans from HMDA will match to our main data set.

3.2 Variable Definitions and Data Cleaning

To create our final panel data set, we clean the raw data in several steps, described in detail in Appendix B. First, we limit the sample to households owned by individuals, excluding institutions and professional investors. Second, for each household, we tag the neighbors within 50 meters, 100 meters, and 250 meters. To measure peer refinance activity, we count the number of neighbors within each distance and in the same census block group that refinanced in the previous quarter. Third, we estimate the current loan-to-value (LTV) ratio for each household each quarter. We assume that borrowers repay following a standard 30-year repayment schedule. To calculate each home's current value, we adjust its 2011 appraised value at the same rate as the median house price in its ZIP code (from Zillow). The quotient gives the estimated current LTV.

We focus on the time period 2008–2012 for two reasons. First, mortgages originated before 1992 are not in our raw data. Using a more recent part of the sample ensures that we know the outstanding mortgage characteristics of all households in the neighborhood. Furthermore, 2008–2012 was marked by both depressed economic activity and very low interest rates, which make it similar in important respects to today's environment and our results relevant for today's policymakers. We next restrict the sample to properties in census blocks that have between five and 100 owner-occupied properties. Blocks with very few or very many households vary too substantially from block to block for our identifying assumption to be valid. Finally, since the real estate agents in our survey suggested that our identifying assumption might be violated in the case of very expensive homes and new construction, we omit these from our sample.

3.3 Summary Statistics

[TABLE 1 HERE]

The final sample contains more than 17 million household-by-quarter observations and is described in detail in Table 1. The average probability of refinancing in a given quarter is 2.4%. The average household has 11 neighbors living within 50 meters, of whom 0.19 refinanced last quarter.

4 Evidence of Hyperlocal Peer Effects

[TABLE 2 HERE]

Table 2 presents our estimations of the linear probability model described by Equation 1. Our first specification estimates the effect of nearby refinances while controlling for a number of characteristics of the outstanding loan (ARM or FRM, refinance or purchase, current LTV, and quarters since origination, co-signer or not) and the property (most recent assessed value, size, and age), all of which might affect the refinance decision. Another potential confound is that households living near to each other might use the same lender and, for example, a lender might introduce a promotion that encourages refinancing. We would then mistake the effect of this promotion for a social influence effect. By including a lender-by-quarter fixed effect, we absorb lender-side effects shared by each lender's borrowers. Estimating this model, we find that each additional neighbor within 50 meters who refinanced in the previous quarter makes the average household 0.432 percentage points or 18% more likely to refinance this quarter.

Importantly, our first specification does *not* include the block group by quarter fixed effect. This omission means that our social influence effect estimate is biased by the effects of both sorting on unobservables and unobserved correlated shocks. When we include this important fixed effect, and assume that the household's nearest neighbors are conditionally random, we control for the effects of endogenous sorting, in which households choose to live near households with similar characteristics, and correlated shocks, where households living near to each other might be similarly influenced to refinance by some external factor. This specification's estimation produces our headline results: Each additional nearby refinance makes households 0.170 percentage points or 7% more likely to refinance. In the third specification, we further control for the household's income, race, and ethnicity. This limits the sample to just those mortgages in the deeds data matched to the HMDA data, but our main result is robust to the inclusion of these demographic controls.

The sample used to estimate our preferred specification includes an average of 808,342 outstanding mortgages, 19,723 of which are refinanced each quarter. And the average household had 0.19 neighbors within 50 meters refinance in the previous quarter. Compared to the counterfactual in which there is no hyperlocal social influence effect, hyperlocal neighbors can be said to cause an additional 808,342 $\times$ 0.0017 $\times$ 0.19 = 260 refinances each quarter. In other words, we estimate that nearly 1.5% of all mortgage refinancing is due to social influence effects from hyperlocal neighbors. If we (i) assume that effect sizes are similar across the United States, and (ii) use the finding in Keys et al. (2016) that the average U.S. household could have saved an average of $11,500 in December 2010 had they refinanced, then we estimate that peer effects save U.S. households over $175 million every quarter.[7]

4.1 Robustness of the Main Result

[TABLE 3 HERE]

In Table 3, we vary our preferred specification in several ways that illustrate the validity of the identifying assumption and demonstrate the robustness of our main result. In the first specification, we drop the block group by quarter fixed effect and instead control directly for the number of peers within 100 meters who refinanced last quarter. This strategy achieves the same central objective as our identification strategy: to control for activity at the neighborhood level and then test if, even within that geography, households behave especially like their closest neighbors, those with whom they are most likely to interact.

An advantage of this specification is that we can zoom in to very fine geographies. That is, we now assume that of the 26 neighbors that a household lives near, the 11 who live *nearest* are randomly assigned. We find that the average household is 0.08 percentage points or 3.3% more likely to refinance if a very nearby neighbor has recently refinanced, controlling for the refinancing activity of those living in a slightly larger area. Specification (4) mimics specification (1) but defines the larger neighborhood with a 250-meter radius instead of a 100-meter one. Ultimately, we prefer specifications that include a geography by time fixed effect as in Table 2 since this absorbs all commonalities between those living in the same area, not just those that actually manifest in different refinancing decisions.

With the concentric circles neighbors in hand, we can combine the two strategies. Specifically, specification (2) adds a tract by quarter fixed effect and specification (3) a block group by quarter

[7] In the fourth quarter of 2010, there were 48,000,000 mortgages outstanding. (See https://www.corelogic.com/downloadable-docs/corelogic-q4-2010-negative-equity-report.pdf, accessed August 13, 2020.) If these households were also 0.0017 × 0.19 percentage points more likely to refinance due to hyperlocal peer effects, then that translates to 15,504 additional mortgages being refinanced at lower rates, saving these households $11,500 each and U.S. households $178,209,000 in total each quarter.

fixed effect. There are two findings of note. First, the “effect” of neighbors with 100 meters diminishes significantly as the geography fixed effects are included. This is entirely expected since the larger concentric circle and the geography fixed effect serve the same purpose in the model – to absorb reasons to refinance shared by people in the same neighborhood, either because of common characteristics of shared exposure to common shocks. Second, the outsized effect of the very nearest peers does *not* change, consistent with households being socially influenced by their especially proximate community.

In the Online Appendix, we explore the concentric circles approach in more detail. In the first specification of Appendix Table C1, we find that the effect of neighbors within 100 meters becomes especially small when the 250-meter disc is also included. However, the effect of the very closest neighbors does not change. This suggests two things. First, the very closest neighbors always matter, consistent with a social influence effect from these neighbors that matters over and above sorting and correlated shocks. Second, the fact that neighbors within 100 meters do not matter much once those within 250 meters are included suggests that endogenous sorting and correlated effects are happening at a geography of at least 250 meters. In other words, we conclude that the large, positive coefficient on neighbors within 50 meters is due to social influence, the large, positive coefficient on neighbors within 250 meters is due to endogenous sorting and correlated shocks, and the relatively small coefficient on neighbors within 100 meters suggests that social influence effects occur at even more local levels while sorting and common shocks are relevant at broader geographies.

An important limitation of our design is one that biases our results toward zero. Households may socially interact with and be influenced by neighbors living in their block group but not within 50 meters (or within 100 meters but not within 50). Our strategy, however, combines the effect of these social interactions with the effects of endogenous group formation and correlated shocks. For this reason, our estimated effects are lower bounds of the true social influence effect of neighbors, since some of these effects are absorbed by the geography fixed effects or larger disc control variables. Appendix Table C2 reaches a similar conclusion. As finer and finer geography fixed effects are included, the estimated coefficient diminishes in magnitude. But even when block-by-quarter fixed effects are included, the estimated coefficient of the social influence effect remains economically and statistically significant. However, as just argued, this estimate is likely biased toward zero since households may socially interact with neighbors outside their closest 11.

Our central assumption is that households do not sort to hyperlocal geographies, and a growing body of evidence suggests this is the case. In Appendix Table C3, we go one step further and use a subsample of Los Angeles in which our assumption is especially likely to hold. Specifically, we limit our sample to the 70% of Los Angeles census blocks that are statistically indistinguishable from their adjacent census blocks. To construct this sample, we compare residents of each block with the residents of those blocks adjacent to it along eight dimensions: the interest rate difference between outstanding loan and prevailing rate, a dummy for a down payment less than 20%, quarters lived there, assessed value, square feet, cosigners, applicant income, and race. Using a T-test for equality of means, we drop any block where more than one of the variables of comparison is significantly different at the 5% level or more than two variables are significantly different at the 10% level. When estimating our main regression on this homogeneous neighborhoods sample, we find that our main results are somewhat smaller, but they are still economically and statistically significant.

Finally, we confirm that our main result is not driven by specific neighborhoods or time periods. In Appendix Table C4, we estimate our main regression year by year going back to 2003. In all years, the effect is important. Appendix Table C5 shows that the effect of neighbors is similar across the house price distribution. Overall, our results consistently point to the importance of the proximate community for households' refinance decisions. Assuming households' immediate neighbors are conditionally random, our findings are evidence of neighbor social influence on one of the household's most important financial decisions.

5 A Word-of-Mouth Channel

Much of the work on neighbor effects has focused on visual inference as a primary channel for information transmission. Foreclosures are typically observable via a bank notice, non-occupancy, or dramatic cuts to home maintenance. Conspicuous consumption is, by definition, salient to neighbors with no face-to-face social interactions required. In our setting, visual influence is unlikely since the decision of whether or not to refinance is very private. In some cases, refinances might be visually observable if they are cash-out refinances used to finance expansions, but these were exceedingly rare during the housing crisis time period of our sample.[8] Instead, we conclude that the hyperlocal neigh-

[8]See the 2013 First Quarter Refinance Report from Freddie Mac online at http://www.freddiemac.com/fmac-resources/research/pdf/RefiReport2013Q1.pdf, accessed May 11, 2020.

bor influence we identify is driven mainly via a word-of-mouth transmission mechanism in which neighbors talk to each other about their financial decisions. To provide more evidence consistent with this channel, we conduct two tests where word-of-mouth social interactions are relatively more or relatively less likely to occur.

5.1 Neighbor Proximity

[FIGURE 1 HERE]

In our first test, presented in Figure 1, we use our preferred geography fixed effect specification and vary the distance between the household and the neighbors of interest.[9] First, we estimate the effect of neighbors living within 50 meters, which corresponds to the first specification in Table 2. Then, in the second specification, we estimate the effect of those neighbors greater than 50 meters away but within 100 meters. We find that when one more of these neighbors refinances, the average household is just 3.7% more likely to refinance in the following quarter, an effect nearly twice as weak as when the refinancing neighbor is within 50 meters. This decreases again to just 2.1% when we look at neighbors within 250 meters but farther than 100 meters away. Neighbors who live nearest are those with whom a given household is most likely to socially interact and therefore most likely to be socially influential by. This is exactly what we find.

5.2 Non-Occupant Owners

In our final test, we investigate the effects of neighbor social influence on a natural falsification group, non-occupant – or "investor" – owners. Recall that our sample omits properties owned by business or professional investors. That is, all properties in our sample are owned by individuals (or couples) who own at most three homes at any one time. We define an owner as a non-occupant if the property address is different than the mailing address where the tax bill is sent. Chinco and Mayer (2016) show that this measure is not perfect, but our hypothesis is that these owners are less likely to occupy the home full-time, are therefore less likely to interact with those living near it, and, consequently, are less likely to be socially influenced to refinance when those living near the home refinance.

[9] See the corresponding regression coefficients in Table C6.

[TABLE 4 HERE]

In the first specification of Table 4, we add investor-owned properties to the sample used previously. We then interact the last quarter refinances of nearby households with a dummy variable equal to 1 if the household is owner occupied. What we find is that households are only socially influenced by their neighbors if they actually live there. Indeed, the main effect of neighbor influence is a fairly precisely estimated zero.

In specification (2), we limit the sample to just homes owned by "investors." Some of these homes are owner occupied, homes that are investors' primary residences, and some of them are not. The main effect of neighbors is now positive, potentially because even non-occupant owners interact with households who live around the second or third home. Importantly, the peer effect nearly triples when the home is occupied by its owner. When interpreting the first specification, one might be concerned that the significant interaction effect is due simply to households who own second and third properties being very different (and perhaps less likely to be socially influenced) than households who own just one. Our second specification allows us to rule out this concern. Since even among the set of households who own multiple properties, occupants are especially likely to be socially influenced.

In the third specification, we take full advantage of the fact that in many instances we observe the investors' primary residences and replace the geography fixed effect with an owner-by-quarter fixed effect. In this way, we look within owner at the two or three properties they own and show that they are more than doubly influenced by the neighbors at their primary residence than their second and third homes.

In both Figure 1 and Table 4, when households are less likely to talk to a neighbor, either because the neighbor lives farther away or because the household does, we find that the social influence effect is weaker. Since refinance decisions are private and in no way visually salient, our body of evidence is most consistent with a social influence effect that requires a word-of-mouth mechanism to propagate.

6 Conclusion

Choosing when to refinance a mortgage is one of the most important decisions a household faces. Furthermore, the decision can be complex, and most households have limited experience and expertise to guide them. Information asymmetry between lenders and borrowers renders traditional sources of influence – the media, the lenders themselves – less reliable, at least from the household's point of view. A natural question emerges: Whom do households turn to for information when deciding whether or not to refinance, and how is this information transferred? In this paper, we look at one source of influence: hyperlocal, neighbor peer groups. Previous work has shown that neighbors do socially influence each other's publicly observable decisions. But there is scant evidence on the importance of neighbor social influence effects on households' private economic decisions.

Using precise data on where households are located, and thus with whom households are more likely to socially interact, we test whether word-of-mouth, social interactions can have a meaningful impact on household financial decision-making. We find that households are 7% more likely to refinance for each additional neighbor within 50 meters who refinanced in the previous quarter. We find that the magnitude of neighbor peer effects are stronger when the neighbors are more proximate. Furthermore, non-occupants, i.e., households who are less likely to interact with their hyperlocal neighbors, show less evidence of being socially influenced. Taken together, our results point to a word-of-mouth, social interaction transmission mechanism and the importance of the proximate community.

Our work has clear implications for policy. The size of potential savings from optimally refinancing can save households thousands of dollars. However, many households fail to refinance. Our results suggest that community-based targeting may be an important strategy to influence households and consequently their neighbors as well. While our work documents that proximate communities do indeed matter, identifying why and exactly how word-of-mouth social influence effects propagate still needs to be better understood. One possibility is that households share their own decisions when they perceive those decisions to have been good to manage impression concerns and make themselves feel smart or helpful as in Berger (2014).

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Figure 1: Effects by Distance

This figure illustrates how the effect of a nearby neighbor's refinance on a household's likelihood of refinancing in a given quarter varies by the distance between the household and the refinancing neighbor. Effect sizes and standard errors are from models estimated in Table C6.

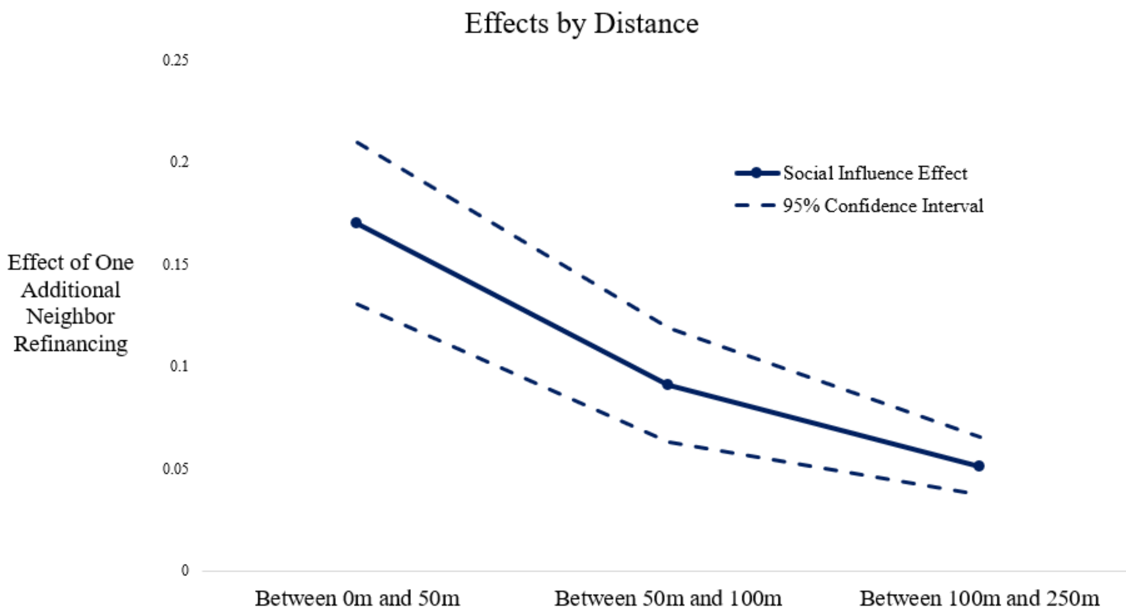

Table 1: Describing the Sample of Households

This table describes the sample that we use for our tests of social influence on the refinance decision. Each quarter, we observe whether or not the household refinanced, the refinancing decisions of their neighbors, and the characteristics of their outstanding loan. We also observe time invariant characteristics about owners and their homes. Adjustable rate mortgages are defined as those with adjustable or graduated interest rates; all mortgages have either adjustable or fixed interest rates. The interest rate difference is the difference between the current interest rate and the rate that was prevailing the year their last mortgage was originated. Current LTV is defined as the estimated outstanding loan balance on the household's primary mortgage divided by the estimated current house price. Co-signer indicates that there are two people on the mortgage contract. The income, race, and ethnicity variables are from HMDA and are defined at the time of the mortgage application. Property characteristics are from the county assessor's office.

	Mean	Std. Dev.	N
Refinanced this Quarter			
Household Refinanced this Quarter (=1)	2.4%	15.2%	17,582,305
Neighborhood Activity			
Nbrs within 50m Refi'd Last Qtr	0.19	0.46	17,582,305
Nbrs within 100m Refi'd Last Qtr	0.52	0.83	17,582,305
Nbrs within 250m Refi'd Last Qtr	2.49	2.51	17,582,305
Nbrs within 50m	10.63	11.27	17,582,305
Nbrs within 100m	25.95	17.90	17,582,305
Nbrs within 250m	117.42	59.88	17,582,305
Outstanding Loan Characteristics			
ARM (=1)	45.1%	49.8%	17,582,305
Refinance (=1)	81.6%	38.7%	17,582,305
Quarters Since Origination	19.2	15.0	17,582,305
Current LTV	76%	54%	17,582,305
Borrower Characteristics			
Co-Signers (=1)	64.5%	47.8%	17,582,305
Owner Occupied (=1)	92.0%	27.2%	17,582,305
Applicant Income (1,000s)	$125	$167	6,620,648
Race, White (=1)	68.7%	46.4%	5,742,885
Ethnicity, Hispanic (=1)	34.9%	47.7%	4,701,331
Property Characteristics			
2011 Assessed Value	$351,484	$353,921	17,582,305
Square Feet	1795	1262	17,582,305

Table 2: Peer Effects on the Decision to Refinance

This table reports the estimated relationship between a household's decision of whether or not to refinance in a given quarter and its peers' recent refinancing decisions. Linear probability models are estimated using the sample described in Table 1 further restricted to just owner-occupied households. Control variables are defined in Table 1. Hispanic is a dummy variable. The race variable is a categorical variable with five categories, Native American is the omitted group. Standard errors are two-way clustered at the census tract and year-quarter level and reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Dependent Variable	Household Refinanced This Quarter (=100)		
Sample	*Owner-Occupied Households*		
	(1)	(2)	(3)
Nbrs within 50m Refi'd Last Qtr	0.432***	0.170***	0.155***
	(0.049)	(0.020)	(0.026)
Number of Neighbors within 50m	-0.0197***	-0.0187***	-0.0184***
	(0.002)	(0.002)	(0.002)
Outstanding Loan is an ARM	-0.859***	-0.892***	-1.110***
	(0.143)	(0.149)	(0.183)
Outstanding Loan is a Refinance	-0.0526	-0.258***	-0.233**
	(0.068)	(0.077)	(0.104)
Co-Signers	0.577***	0.523***	0.632***
	(0.046)	(0.043)	(0.065)
Natural Log 2011 Assessed Value	0.657***	0.0677	0.111
	(0.122)	(0.073)	(0.165)
Natural Log Square Feet	0.570***	0.585***	0.776***
	(0.049)	(0.049)	(0.087)
Current LTV	-0.00302***	-0.00426***	-0.00462***
	(0.001)	(0.001)	(0.001)

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Home Built 1931-1950	0.293***	-0.0479**	-0.0619
	(0.047)	(0.023)	(0.046)
Home Built 1951-1970	0.218***	-0.238***	-0.226***
	(0.062)	(0.026)	(0.059)
Home Built 1971-1980	-0.208**	-0.700***	-0.648***
	(0.074)	(0.048)	(0.076)
Home Built 1981-1990	-0.580***	-0.870***	-0.785***
	(0.073)	(0.064)	(0.082)
Home Built 1991-2000	-0.623***	-0.748***	-0.665***
	(0.075)	(0.065)	(0.075)
Home Built 2001-	-0.677***	-0.662***	-0.524***
	(0.092)	(0.078)	(0.110)
Natural Log Owner Income			-0.141**
			(0.060)
Hispanic			-0.324***
			(0.053)
Asian			0.177*
			(0.101)
Black			-0.271***
			(0.066)
Pacific Islander			-0.234**
			(0.096)
White			-0.0556
			(0.054)
Fixed Effects			
Quarters Since Last Mortgage	Y	Y	Y
Outstanding Lender × Quarter	Y	Y	Y
Block Group × Quarter		Y	Y
N	16,166,843	16,166,526	3,826,715
Sample Means			
Refi'd This Quarter	2.44	2.44	2.87
Nbrs within 50m Refi'd Last Qtr	0.19	0.19	0.20

Table 3: A Concentric Circles Design

This table reports the estimated relationship between a household's decision of whether or not to refinance in a given quarter and its peers' recent refinancing decisions. Linear probability models are estimated using the sample described in Table 1 further restricted to just owner-occupied households. Control variables are defined in Table 1 and include all variables included in the first and second specification in Table 2. Standard errors are two-way clustered at the census tract and year-quarter level and reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Dependent Variable	Household Refinanced This Quarter (=100)					
Sample	*Owner-Occupied Households*					
	(1)	(2)	(3)	(4)	(5)	(6)
Nbrs within 50m Refi'd Last Qtr	0.0801***	0.0878***	0.0829***	0.140***	0.129***	0.120***
	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)
Nbrs within 100m Refi'd Last Qtr	0.313***	0.122***	0.0889***			
	(0.039)	(0.018)	(0.014)			
Nbrs within 250m Refi'd Last Qtr				0.169***	0.0761***	0.0615***
				(0.021)	(0.010)	(0.008)
CoreLogic Controls	Y	Y	Y	Y	Y	Y
Fixed Effects						
Quarters Since Last Mortgage	Y	Y	Y	Y	Y	Y
Outstanding Lender × Quarter	Y	Y	Y	Y	Y	Y
Tract × Quarter		Y			Y	
Block Group × Quarter			Y			Y
N	16,166,843	16,166,690	16,166,526	16,166,843	16,166,690	16,166,526
Sample Means						
Refi'd This Quarter	2.44	2.44	2.44	2.44	2.44	2.44
Nbrs within 50m Refi'd Last Qtr	0.19	0.19	0.19	0.19	0.19	0.19

Table 4: Non-Occupant Owners

This table reports the estimated relationship between a household's decision of whether or not to refinance in a given quarter and its peers' recent refinancing decisions. Specification (1) mimics the second specification in Table 2 but uses a larger sample that includes non-owner occupied homes. Specifications (2) and (3) use only the sample of "investor"-owned properties, those properties whose owners own either two or three properties simultaneously. Control variables are defined in Table 1 and include all variables included in the first and second specification in Table 2. Standard errors are two-way clustered at the census tract and year-quarter level and reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Dependent Variable	Household Refinanced This Quarter (=100)		
Sample	*All Households*	*'Investor' Owned Households*	
	(1)	(2)	(3)
Nbrs within 50m Refi'd Last Qtr × Owner Occupied	0.166***	0.195**	0.235**
	(0.042)	(0.073)	(0.091)
Nbrs within 50m Refi'd Last Qtr	0.0156	0.110*	0.155**
	(0.037)	(0.057)	(0.062)
Owner Occupied	0.569***	0.469***	0.653***
	(0.058)	(0.045)	(0.061)
CoreLogic Controls	Y	Y	Y
Fixed Effects			
Quarters Since Last Mortgage	Y	Y	Y
Outstanding Lender × Quarter	Y	Y	Y
Block Group × Quarter	Y	Y	
Owner × Quarter			Y
N	17,582,305	1,828,172	1,159,277
Sample Means			
Refi'd This Quarter	2.36	1.74	1.66
Nbrs within 50m Refi'd Last Qtr	0.19	0.17	0.17

ONLINE APPENDIX

"Household Mortgage Refinancing Decisions are Neighbor Influenced"

February 2021

This is the Online Appendix for "Household's Mortgage Refinancing Decisions Are Neighbor Influenced."

- Appendix A describes the phone interviews with real estate agents.
- Appendix B describes the data cleaning in more detail.
- Appendix C contains the supplemental tables.

A Phone Interviews

We conducted phone interviews with 41 real estate agents operating in the Los Angeles area in order to determine how precisely located home buyer location preferences were in their experience. More specifically, we asked how broad an area clients considered when buying a home, whether they sought a home on a precise block, and if so, what the determinants of wanting to buy a house on a specific block were. Thirty-seven of the 41 (92.7%) real estate agents reported that clients typically looked in a few neighborhoods within about an eight to thirteen block radius. The other four real estate agents, who notably focused more on high-end real estate (above $2 million), reported that some clients were focused on a particular block as they were looking for prestigious addresses or were interested in a new development. As a direct result of these interviews, we ensure that the sample on which we estimate our models excludes highly priced homes and new construction and development. Note that, in the event households choose areas even larger than block-plus-adjacent-block neighborhoods (as our survey of real estate agents suggests they do), then our assumption is especially valid. For example, if households choose within a 10 block radius where to live, then both block peers and our definition of neighborhood peers will be randomly assigned conditional on 10-block radius neighbors. We therefore view our working definition of neighborhood (block plus only adjacent blocks) as a conservative one.

B Data Cleaning

To construct the data set necessary for estimating our models, we undertake the following steps. First, we ensure that we have a sample of households, as opposed to institutions or professional investors. We use the name cleaning algorithm developed by Bayer et al. (2021) to tag borrowers as either individuals or institutions. This algorithm uses the names of the borrowers and a rich set of keywords to determine if the borrowers are trusts, banks, businesses, government and nonprofit organizations, or individuals. The algorithm further cleans and standardizes the names of the first borrower and, if the loan has a co-signer, the second borrower. We limit our sample to only those properties owned by individuals – as opposed to institutions – and further drop any homeowners who ever concurrently own four or more properties (for more on this interesting group of buyers see Bayer et al. (2021)).

Second, we create a novel algorithm that assigns to each homeowner the property that it occupies. This algorithm takes as its key inputs the mailing address used at the time the loan was originated, site address of the property securing the loan, and purpose of the loan. We follow each homeowner by property over time and say that the house is not occupied if its mortgage is refinanced with different site and mailing addresses and is occupied if they are the same. Then, if the homeowners only ever own one home, we say that the home is owner occupied. Next, if we see they occupy one property, we say they do not occupy any others. Finally, we assume that the property they purchased first is occupied, and any others purchased later are not. This algorithm is important as our analysis hinges on social interactions. We use owner-occupant status to identify primary residences, where owners are more likely to be interacting with their neighbors.

Third, we group all refinancing activity together (e.g., refinances that replace existing loans, cash-out refinances, home equity loans, and home equity lines of credit). We follow households over time and observe, each quarter, if they originated a new loan of one of these types. If they did, we say that they refinanced.

Fourth, we use the latitude and the longitude of the property to precisely map the universe of owner-occupied homes in Los Angeles County, outstanding mortgage loans, and new mortgage transactions. Using ArcGIS, a geographic information system, we map each property into exactly one census block. Census blocks are the smallest geographic unit defined by the census. In Los Angeles, they are roughly similar to city blocks and populated by an average of 16 owner-occupied households.

Finally, we focus on the time period 2008-2012 for two reasons. First, from a research design standpoint, an important part of our analysis relies on knowing the outstanding mortgage characteristics of all households in the neighborhood. We cannot see mortgages originated before 1992. While this potentially can lead to a missing data problem, focusing on the later end of the sample diminishes the proportion of mortgages that were originated prior to 1992. Second, this time period was marked by both depressed economic activity and very low interest rates, which makes it similar in important respects to the current time period and can therefore potentially be a guide for the future.

We further drop observations in which the property securing the loan is a condominium or was divided into smaller properties and resold. We also drop transactions if 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. We keep only mortgage loans written to individuals, as opposed to trusts or businesses, and further drop all properties owned by homeowners who concurrently hold four or more properties. We drop observations that are missing key information including the location of the property, the name of the buyer, the lender (allowing us to control for lender-level fixed effects), the amount of the loan, square footage, or an assessed value. We drop homes assessed at more than $2,000,000, which drops a further 154 properties. Finally, we drop from the sample any loans originated by lenders that made fewer than 1,000 loans over the entire time series.

C Supplemental Tables

Table C1: A Concentric Circles Approach

This table reports the estimated relationship between a household's decision of whether or not to refinance in a given quarter and its peers' recent refinancing decisions. Linear probability models are estimated using the sample described in Table 1 further restricted to just owner-occupied households. Control variables are defined in Table 1 and include all variables detailed in the second specification in Table 2. Standard errors are two-way clustered at the census tract and year-quarter level and reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Dependent Variable	Household Refinanced This Quarter (=100)		
Sample	*Owner-Occupied Households*		
	(1)	(2)	(3)
Nbrs within 50m Refi'd Last Qtr	0.102***	0.0801***	0.140***
	(0.014)	(0.013)	(0.015)
Nbrs within 100m Refi'd Last Qtr	0.0429***	0.313***	
	(0.008)	(0.039)	
Nbrs within 250m Refi'd Last Qtr	0.163***		0.169***
	(0.020)		(0.021)
CoreLogic Controls	Y	Y	Y
Fixed Effects			
Quarters Since Last Mortgage	Y	Y	Y
Outstanding Lender × Quarter	Y	Y	Y
N	16,166,843	16,166,843	16,166,843
Sample Means			
Refi'd This Quarter	2.44	2.44	2.44
Nbrs within 50m Refi'd Last Qtr	0.19	0.19	0.19

Table C2: Varying the Geography Fixed Effect

This table reports the estimated relationship between a household's decision of whether or not to refinance in a given quarter and its peers' recent refinancing decisions. Linear probability models are estimated using the sample described in Table 1 further restricted to just owner-occupied households. Control variables are defined in Table 1 and include all variables detailed in the second specification in Table 2. Standard errors are two-way clustered at the census tract and year-quarter level and reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Dependent Variable	Household Refinanced This Quarter (=100)		
Sample	*Owner-Occupied Households*		
	(1)	(2)	(3)
Nbrs within 50m Refi'd Last Qtr	0.214***	0.170***	0.0831***
	(0.026)	(0.020)	(0.012)
CoreLogic Controls	Y	Y	Y
Fixed Effects			
Quarters Since Last Mortgage	Y	Y	Y
Outstanding Lender × Quarter	Y	Y	Y
Tract × Quarter	Y		
Block Group × Quarter		Y	
Block × Quarter			Y
N	16,166,690	16,166,526	16,150,385
Sample Means			
Refi'd This Quarter	2.44	2.44	2.44
Nbrs within 50m Refi'd Last Qtr	0.19	0.19	0.19

Table C3: Homogeneous Neighborhoods

This table reports the estimated relationship between a household's decision of whether or not to refinance in a given quarter and its peers' recent refinancing decisions. Linear probability models are estimated using the sample described in Table 1 further restricted to just owner-occupied households and census blocks statistically indistinguishable from their surrounding census blocks. Control variables are defined in Table 1. Standard errors are two-way clustered at the census tract and year-quarter level and reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Dependent Variable	Household Refinanced This Quarter (=100)		
Sample	*Owner-Occupied Households*		
	(1)	(2)	(3)
Nbrs within 50m Refi'd Last Qtr	0.422***	0.121***	0.104***
	(0.053)	(0.018)	(0.027)
CoreLogic Controls	Y	Y	Y
HMDA Controls			Y
Fixed Effects			
Quarters Since Last Mortgage	Y	Y	Y
Outstanding Lender × Quarter	Y	Y	Y
Block Group × Quarter		Y	Y
N	11,206,461	11,206,168	2,686,039
Sample Means			
Refi'd This Quarter	2.49	2.49	2.91
Nbrs within 50m Refi'd Last Qtr	0.19	0.19	0.20

Table C4: Homogeneity of the Effect Size Over Time

This table reports the estimated relationship between a household's decision of whether or not to refinance in a given quarter and its peers' recent refinancing decisions. Linear probability models are estimated using the sample described in Table 1 further restricted to just owner-occupied households. Control variables are defined in Table 1 and include all variables detailed in the second specification in Table 2. Standard errors are two-way clustered at the census tract and year-quarter level and reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Dependent Variable	Household Refinanced This Quarter (=100)									
Sample	*Owner-Occupied Households*									
Subsample, Years	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nbrs within 50m Refi'd Last Qtr	0.176***	0.0580**	0.0917***	0.0785**	0.162**	0.131**	0.179**	0.240**	0.135**	0.158**
	(0.029)	(0.016)	(0.015)	(0.024)	(0.041)	(0.028)	(0.032)	(0.066)	(0.027)	(0.048)
CoreLogic Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects										
Quarters Since Last Mortgage	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Outstanding Lender × Quarter	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Block Group × Quarter	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	2,133,039	2,417,551	2,652,140	2,790,388	2,970,306	3,194,793	3,263,633	3,266,491	3,242,501	3,199,108
Sample Means										
Refi'd This Quarter	13.65	9.93	8.73	6.91	4.85	2.09	2.22	2.50	2.52	2.85
Nbrs within 50m Refi'd Last Qtr	1.06	0.86	0.74	0.65	0.42	0.21	0.15	0.16	0.18	0.25

Table C5: Homogeneity of the Effect Size over Local House Prices

This table reports the estimated relationship between a household's decision of whether or not to refinance in a given quarter and its peers' recent refinancing decisions. Linear probability models are estimated using the sample described in Table 1 further restricted to just owner-occupied households. Control variables are defined in Table 1 and include all variables detailed in the second specification in Table 2. Standard errors are two-way clustered at the census tract and year-quarter level and reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Dependent Variable	Household Refinanced This Quarter (=100)				
Sample	*Owner-Occupied Households*				
Subsample, Tract Avg HP	*Least*	*2*	*3*	*4*	*Most*
	(1)	(2)	(3)	(4)	(5)
Nbrs within 50m Refi'd Last Qtr	0.117***	0.0885***	0.105***	0.128***	0.156***
	(0.019)	(0.025)	(0.020)	(0.021)	(0.022)
CoreLogic Controls	Y	Y	Y	Y	Y
Fixed Effects					
Quarters Since Last Mortgage	Y	Y	Y	Y	Y
Outstanding Lender × Quarter	Y	Y	Y	Y	Y
Block Group × Quarter	Y	Y	Y	Y	Y
N	6,018,708	6,403,805	7,201,419	7,236,549	6,796,652
Sample Means					
Refi'd This Quarter	3.78	4.12	4.31	4.50	4.80
Nbrs within 50m Refi'd Last Qtr	0.39	0.44	0.46	0.49	0.43
House Price	$194,440	$244,530	$300,454	$398,502	$827,691

Table C6: Increasing Radii

This table reports the estimated relationship between a household's decision of whether or not to refinance in a given quarter and its peers' recent refinancing decisions. Linear probability models are estimated using the sample described in Table 1 further restricted to just owner-occupied households. Control variables are defined in Table 1 and include all variables detailed in the second specification in Table 2. Standard errors are two-way clustered at the census tract and year-quarter level and reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Dependent Variable	Household Refinanced This Quarter (=100)		
Sample	*Owner-Occupied Households*		
	(1)	(2)	(3)
Nbrs within 50m Refi'd Last Qtr	0.170***		
	(0.020)		
Nbrs between 50m and 100m Refi'd Last Qtr		0.091***	
		(0.014)	
Nbrs between 100m and 250m Refi'd Last Qtr			0.051***
			(0.007)
CoreLogic Controls	Y	Y	Y
Fixed Effects			
Quarters Since Last Mortgage	Y	Y	Y
Outstanding Lender × Quarter	Y	Y	Y
Block Group × Quarter	Y	Y	Y
N	16,166,526	16,166,526	16,166,526
Sample Means			
Refi'd This Quarter	2.44	2.44	2.44
Nbrs Refi'd Last Qtr	0.19	0.33	2.00