SOCIAL NETWORKS AND HOUSING MARKETS*

Michael Bailey† Ruiqing Cao‡ Theresa Kuchler§ Johannes Stroebel¶

Abstract

We analyze the effects of social interactions on housing market expectations and investments. Our data combine anonymized social network information from Facebook with housing transaction data and a survey. Variation in the geographic spread of social networks, combined with time-varying regional house price changes, induces heterogeneity in the house price experiences of different individuals' friends. Individuals whose geographically distant friends experienced larger recent house price increases are more likely to transition from renting to owning. They also buy larger houses, and pay more for a given house. Similarly, when homeowners' friends experience less positive house price changes, these homeowners are more likely to become renters, and more likely to sell their property at a lower price. We find that these relationships are driven by the effect of social interactions on individuals' housing market expectations, and present evidence against competing explanations. Indeed, survey data show that individuals whose geographically distant friends experienced larger recent house price increases consider local property a more attractive investment, with bigger effects for individuals who regularly discuss such investments with their friends.

JEL Codes: G12, D12, D14, D84, R21

Keywords: Social Networks, Expectation Formation, Disagreement, House Price Dynamics

*This version: December 19, 2016. For helpful comments and discussions, we are grateful to Tony Cookson, Eduardo Davila, Anthony DeFusco, Giovanni Favara, Andreas Fuster, Marty Eichenbaum, Xavier Gabaix, Pedro Gete, Stefano Giglio, Adam Guren, Ben Golub, Harrison Hong, Erik Hurst, Anil Kashyap, Ben Keys, Andres Liberman, Guido Lorenzoni, Michael Luca, Brigitte Madrian, Ulrike Malmendier, Holger Mueller, Stijn van Nieuwerburgh, Cecilia Parlatore, Alp Simsek, Andrei Shleifer, Joe Vavra, Andreas Weber, Arlene Wong, Wei Xiong, Basit Zafar, and Eric Zwick, four anonymous referees, as well as seminar and conference participants at Harvard, Harvard Business School, NYU, Northwestern, University of Chicago, University of Minnesota, UC Berkeley, UC Davis, Penn State, the University of British Columbia, the Federal Reserve Banks of San Francisco, Philadelphia, and New York, the Consumer Financial Protection Bureau, the FCA, Baruch, CHUM, SED, NBER Summer Institute (Behavioral Macro, Impulse & Propagation, Digitization, Household Finance, Real Estate), NBER Behavioral Finance, Stanford Institute for Theoretical Economics, Mannheim University, Frankfurt University, and the Christmas Meeting of German Economists Abroad. We thank the Center for Global Economy and Business at NYU Stern for generous research support. This research was facilitated through a research consulting agreement between the academic authors and Facebook. This research cooperation was established to allow researchers to collaborate with Facebook in order to exploit anonymized data sets based on Facebook's unique data asset to address questions of policy importance.

†Facebook. Email: mcbailey@fb.com

‡Harvard University. Email: ruiqingcao@fas.harvard.edu

§New York University, Stern School of Business. Email: tkuchler@stern.nyu.edu

¶New York University, Stern School of Business, NBER, and CEPR. Email: johannes.stroebel@nyu.edu

Social interactions play a prominent role in our understanding of many economic and social phenomena. For example, social networks can influence labor market outcomes by providing information to job seekers and facilitating screening by employers. They have also been shown to affect individuals' decision making across a variety of other settings, from whether to commit a crime to the choice of which movie to watch.[1] Similarly, researchers have conjectured that interactions through social networks can influence housing market dynamics, with such interactions providing a mechanism through which optimism or pessimism about future house price growth can spread through the population (e.g., Akerlof and Shiller, 2010; Shiller, 2015; Bayer, Geissler, Mangum, and Roberts, 2016; Burnside, Eichenbaum, and Rebelo, 2016). However, providing empirical support for the quantitative importance of these and other narratives of the role of social interactions in economics has proved challenging, in large parts due to the absence of comprehensive and representative data on individuals' social networks that can be linked to outcome variables of interest.

In this paper, we show how newly emerging data from online social networks can overcome this measurement challenge, and help researchers better understand both the structure of real-world social networks, as well as their effects on economic and financial decision making. In particular, we explore anonymized data on friendship networks from Facebook, the largest online social network, with 229 million active users in the U.S. and Canada, and 1.8 billion users globally. We combine these social network data with anonymized individual-level housing transaction data from Los Angeles and a housing expectations survey. We analyze these data to investigate the effect of social networks on housing investment behavior. We show that, through social interactions, the recent house price experiences within an individual's social network affect her perceptions of the attractiveness of property investments, and through this channel have large effects on her housing market activity.

Our analysis starts by documenting that, at any point in time, different people in the same local housing market have friends that have experienced vastly different recent house price movements. For example, the average 2008-2010 house price changes experienced by the social networks of our Los Angeles sample population ranged from -10.1% at the 5th percentile of the distribution, to -5.2% at the 95th percentile of the distribution. When focusing only on the experiences of friends that live outside of the Los Angeles commuting zone, this variation is even larger, with house price experiences ranging between -16.3% at the 5th percentile and -5.2% at the 95th percentile of the distribution.

To better understand the sources of this variation, we explore the geographic dimension of the social networks in our data. We observe more than 300 U.S.-based friends for the average individual in our Los Angeles sample. There is significant geographic clustering of friendship links to close-by individuals: the average person in our sample has 65.5% of her friendship links with individuals living within 200 miles. Despite this geographic clustering, we find that the individuals in our sample are exposed to many different housing markets across the United States. Indeed, the median person has friends in 37 different counties. There is substantial variation across our sample in the geographic

[1] See Ioannides and Datcher Loury (2004), Montgomery (1991), Glaeser, Sacerdote, and Scheinkman (1996), and Moretti (2011), respectively. Granovetter (2005) and Jackson (2014) survey the literature on social networks in economics.

structure of social networks. At the 95$^{\text{th}}$ percentile of the distribution, over 88.6% of friends live within 200 miles, while at the 5$^{\text{th}}$ percentile, only 23.9% of friends do. Some of this heterogeneity in network characteristics is systematically related to observable individual characteristics. For example, richer, older, and better-educated people have less geographically concentrated social networks. We also observe significant variation in the exposure to different U.S. regional housing markets across our Los Angeles sample. For example, the 5-95 percentile range across our sample in the share of out-of-commuting zone friends living in the Mid-Atlantic Census Division is 0% to 34.3%. It is this variation in the location of individuals' friends, combined with time-varying regional house price changes, that explains the differences across individuals in their friends' house price experiences.

In our empirical analysis, we want to isolate the causal effect of this variation in house price experiences of different individuals' friends on these individuals' own housing market investments. We also want to explore various mechanisms that could explain a causal relationship. To measure an individual's housing investment decisions, we combine the social network information from Facebook with anonymized public-record data on individuals' housing transactions for Los Angeles. Our final sample contains anonymized data on 1.4 million individuals and 525,000 housing transactions. We use these combined data to analyze the effects of the house price experiences in an individual's social network on three aspects of her housing market investment behavior: the extensive margin decision (i.e., whether to rent or own), the intensive margin decision (i.e., the square footage of properties bought), and the willingness to pay for a particular house.

In order to isolate a *causal* relationship between friends' house price experiences and own housing market investments, we need to address a number of identification challenges. In particular, we have to rule out other, non-causal explanations of any observed correlation between friends' house price experiences and own housing investment behavior. The first of these challenges derives from the fact that people differ systematically in how many local friends they have. Those individuals with more local friends will have own house price experiences that mechanically correlate more with those of their friends. To the extent that these individuals might also be more likely to extrapolate from their own house price experiences when forming expectations about future house price growth, any correlation between own investment behavior and the house price experiences across all friends might just be picking up these extrapolative expectations rather than a causal effect through social interactions. Therefore, to remove confounding effects from a possible extrapolation of own house price experiences, we instrument for the house price experiences in the full network with the experiences of friends in geographically distant housing markets. We also ensure that our results are not driven by individuals who recently moved from those distant locations to Los Angeles.

Using this instrumental variables strategy, we document that the house price experiences within an individual's social network have a quantitatively large effect on all three aspects of her housing investment decision. First, a five percentage point higher average house price change between 2008 and 2010 in the counties where an individual's friends live leads to a 3.0 percentage point increase in the probability of that individual transitioning from being a renter in 2010 to being a homeowner in 2012, relative to a baseline transition probability of 18%. This is more than half of the size of the effect of adding a family member. We also find that homeowners are more likely to transition to renting when their friends experience below-average house price changes. Second, conditional on an individual buying a property, a five percentage point increase in friends' house price experiences over the 24 months prior to the purchase is associated with the individual buying a 1.6 percent larger property. Third, conditional on observable property characteristics, a five percentage point increase in the house price experiences in an individual's social network is associated with that individual paying 2.3 percent more for the same property. This result is robust to adding property fixed effects to account for unobservable property characteristics. When we also control for the house price movements in the seller's network, we find that sellers whose friends experienced higher house price appreciations also demand higher sales prices.

As described above, we argue that these relationships between the house price experiences in an individual's social network and her housing market behavior capture a causal mechanism. In addition to using our instrumental variables strategy to abstract from a possible extrapolation of own house price experiences, we rule out a number of alternative non-causal explanations of our estimates.

In particular, we address possible challenges coming from the non-random exposure of individuals to different geographically distant housing markets. We first show that a correlation between where an individual has friends and her own characteristics does not, by itself, confound our findings. This is because the house price experiences within an individual's social network are affected by the *interaction* of the geographic distribution of her friends and how house prices in those areas move in a given year. While people with friends in Boston are different from people with friends in Miami, relative house price movements in Miami and Boston change over time. Indeed, we verify that the average house price experience of a person's friends over time does not vary with that person's characteristics. Comparing the housing investment behavior of individuals with friends in Boston across different years thus allows us to remove any time-invariant confounding effect of the geographic distribution of an individual's friends. In fact, in some specifications we observe multiple transactions of the same individual across different years. We find that this same individual is willing to pay more for a given house in years following stronger relative house price growth in her social network.

However, despite the fact that friends' house price experiences do not vary with individual characteristics *on average*, one might still be concerned that unobserved shocks to an individual's ability or desire to buy a house in a given year might be correlated with her friends' house price experiences *in that year* through a channel other than social interactions. This challenge is much weaker than that encountered by the peer effects literature, which has to establish that correlated behavior does not arise from correlated shocks to friendship groups (Manski, 1993). In our setting, alternative interpretations require a shock to an individual's ability or desire to buy a house in a given local housing market that contemporaneously *moves house prices* in geographically distant regions where she has friends. We address the one such potential force that we were able to identify. In particular, many people have friends that work in the same sector. If economic activity in that sector features significant geographic clustering (e.g., tech in Silicon Valley), positive shocks to that sector in a given year might both enable an individual to buy a house, and drive up aggregate house prices in those sector-exposed regions where the individual has friends. To rule out this alternative explanation, we show that all results are robust to restricting the sample to individuals that are retired or work in geographically non-clustered professions (e.g., teachers). Our results are also robust to directly including controls for the economic conditions affecting a person's social network, and to interacting our large set of individual demographics with year fixed effects, which allows, for example, the effect of different education levels or different occupations on behavior to vary over time.

After ruling out these and other non-causal interpretations of the observed relationship between the house price experiences of an individual's friends and her own housing investment behavior, we explore which channels might explain the observed effect.

We first provide evidence for an important effect of social interactions on an individual's assessment of the attractiveness of property investments, which would naturally affect her housing market investment behavior. To do this, we analyze 1,242 responses to a housing market survey among Los Angeles-based Facebook users. Over half of the survey respondents report regularly talking to their friends about investing in the housing market. The survey also asked respondents to assess the attractiveness of property investments in their own zip code relative to other financial investments. Holding respondent characteristics fixed, we find a strong relationship between recent house price movements in counties where a respondent has friends, and whether that respondent believes that local property is a good investment. Importantly, the relationship between the house price experiences in an individual's social network and her assessment of the attractiveness of local property investments is stronger for individuals who regularly talk to their friends about investing in property. These results suggest that social interactions provide a link between friends' house price experiences and an individual's own housing market expectations, and highlight a plausible channel through which these experiences could causally affect individuals' housing market investments.

Why would an individual's beliefs about the attractiveness of housing investments be affected by the house price experiences of her friends? While our analysis does not allow us to distinguish between all possible explanations for this type of behavior, we present some evidence that suggests it is unlikely to be the result of purely rational learning. First, the investment response to friends' house price experiences is independent of how predictive a person's social network house price experience is for future house price movements in Los Angeles; the effect also does not vary with the geographic dispersion of the network, as one might expect if individuals were trying to learn about some national house price component from the experiences of their friends. In addition, we find the effect to be weakly declining in education levels. However, there remain a number of possible explanations. For example, our findings could be due to the spread of irrational sentiments (Akerlof and Shiller, 2010;

Shiller, 2015; Burnside, Eichenbaum, and Rebelo, 2016), or due to overconfidence, with individuals over-reacting to noisy signals they receive through their social networks (Barberis and Thaler, 2003).

We also consider a number of alternative channels that might explain the causal effect of the house price movements experienced by an individuals' friends and her own housing investment behavior. However, we are unable to find evidence for the presence of other channels. First, we document that our results are not driven by individuals investing more in real estate as the value of their expected housing bequest increases with the house price gains of their geographically distant family members. Second, we show that our findings cannot be explained by a story of consumption externalities, such as a desire to "keep up with the Joneses." Lastly, we rule out that the observed findings are driven by a desire of individuals to hedge against house price growth in areas they eventually desire to move to.

Overall, our results provide strong evidence for a causal effect of friends' house price experiences on individuals' housing market behavior that comes primarily through affecting those individuals' beliefs about the attractiveness of housing investments. In follow-on work, Bailey, Cao, Kuchler, Stroebel, and Vavra (2016a) show that the individual-level effects documented in this paper aggregate up to affect county-level prices and trading volumes.

We view our paper as making three contributions. First, we show how newly-emerging data from online social networks can help researchers to better understand the structure of individual-level and aggregate social networks. We also demonstrate how such data can be used to investigate the effects of interactions through social networks on economic and financial decision making. In related work, Bailey, Cao, Kuchler, Stroebel, and Wong (2016b) aggregate social network data from Facebook to produce a county-level "Social Connectedness Index." They use these data to document that other indicators of social and economic activity that can be measured at the county- or state-level, such as trade flows, migration, and patent citations, are also correlated with the structure of social networks.

Our second contribution is to document that differences in friends' house price experiences are an important source of heterogeneity in individuals' housing market expectations. This result contributes to a research effort analyzing how people form expectations about economic outcomes. One popular explanation is that such expectations depend on own experiences. For example, Kuchler and Zafar (2015) show that past local house price changes influence individuals' expectations of future national house price changes. Guren (2015), Glaeser and Nathanson (2015), and Barberis, Greenwood, Jin, and Shleifer (2015) explore the implications of such extrapolation for price dynamics. Recent experiences or events also affect expectations in other settings (e.g., Vissing-Jorgensen, 2003; Malmendier and Nagel, 2011, 2015; Choi, Laibson, Madrian, and Metrick, 2009; Greenwood and Shleifer, 2014). We expand on this literature, by showing that individuals' expectations are not just affected by their own experiences, but also by the recent experiences of their friends. These results suggest that differences in social networks provide a quantitatively important explanation for disagreement about asset values among investors.[2] Our findings also provide empirical support for theories in which communication

[2] In related work, Cookson and Niessner (2016) analyze messages posted to an online investment community to understand the sources of disagreement about stock valuations among the users of that website.

between agents propagates shocks to expectations, in particular in the housing market (e.g., Akerlof and Shiller, 2010; Acemoglu, Dahleh, Lobel, and Ozdaglar, 2011; Angeletos and La'O, 2013; Shiller, 2015; Burnside, Eichenbaum, and Rebelo, 2016).

Our third contribution is to show that individuals with friends that experienced more positive recent house price changes, and who thus believe that housing is a more attractive investment, actually do invest more in real estate, and are willing to pay more for a given house. These findings provide support for an important class of models in which expectation heterogeneity influences asset valuations and motivates individuals to trade (e.g., Miller, 1977; Harrison and Kreps, 1978; Hong and Stein, 1999, 2007; Scheinkman and Xiong, 2003; Geanakoplos, 2009; Simsek, 2013a,b; Brunnermeier, Simsek, and Xiong, 2014). Most directly, our findings provide evidence for a number of papers that focus on the role of heterogeneous expectations and shifts between optimism and pessimism about future house price growth in causing price fluctuations and trading volume in the housing market (see, for example, Piazzesi and Schneider, 2009; Favara and Song, 2014; Landvoigt, 2014; Nathanson and Zwick, 2014; Berger, Guerrieri, Lorenzoni, and Vavra, 2015; Kaplan, Mitman, and Violante, 2015).

The paper proceeds as follows: Section 1 describes the data and presents extensive summary statistics on the social networks of the individuals in our sample. Section 2 describes our empirical approach for identifying a causal effect of friends' house price experiences on own behavior. Section 3 explores the relationship between the average house price experiences in an individual's social network and that individual's housing market investments. Section 4 investigates various mechanisms for explaining the observed causal effect. The final section concludes.

1 Data Description and Empirical Approach

In this paper, we provide empirical evidence for a causal effect of friends' house price experiences on a person's own housing investment behavior. To do this, we have to overcome both a measurement challenge ("how do we measure social networks and housing investment behavior in the data?"), and a number of identification challenges ("how can we rule out other, non-causal explanations of any observed correlation between friends' house price experiences and own housing investment behavior?"). In this section, we describe how we overcome the measurement challenge by combining a number of anonymized data sets that contain information about individual housing market participants, including data on their social networks and their property transactions. We also provide descriptive statistics on the social networks we observe in our sample.

1.1 Data Sets

The key measurement challenge that pervades the empirical literature studying social networks is the difficulty of observing, at a large scale, which individuals are connected to each other. In this paper, we overcome this challenge by working with anonymized social network data from Facebook. Facebook was created in 2004 as a college-wide online social network for students to maintain a profile and communicate with their friends. It has since grown to become the world's largest online social networking service, with over 1.8 billion monthly active users globally, and 229 million monthly active users in the U.S. and Canada (Facebook, 2016). Our baseline data include a de-identified snapshot of all U.S.-based active Facebook users from July 1, 2015. For these users, we observe demographic information, such as their age, education, and county of residence, as well as the set of other Facebook users they are connected to. Using the language adopted by the Facebook community, we call these connections "friends." Indeed, in the U.S., Facebook serves primarily as a platform for real-world friends and acquaintances to interact online, and people usually only add connections to individuals on Facebook whom they know in the real world (Jones, Settle, Bond, Fariss, Marlow, and Fowler, 2013; Gilbert and Karahalios, 2009; Hampton, Goulet, Rainie, and Purcell, 2011). This suggests that our data allow us to measure which U.S. housing markets different individuals are exposed to through their real-world social networks.

To construct a measure of the house price experiences in different individuals' social networks, which will be the key explanatory variable in our empirical analysis, we combine the data on the county of residence of different individuals' friends with county-level house price indices from Zillow. In particular, let $ShareFriends_{i,N,c}$ measure the share of person i's friends in network N that lives in county c. Similarly, let $\Delta HP_{c,t_1,t_2}$ capture the house price changes in county c between t_1 and t_2. We then construct our main explanatory variable as:

$$FriendHPExp^{N}_{i,t_1,t_2} = \sum_{c} ShareFriends_{i,N,c} \times \Delta HP_{c,t_1,t_2}, \qquad (1)$$

This measure of friends' house price experiences can be constructed for different networks N of individual i. The broadest such network includes all of individual i's Facebook friends, but other sub-networks might include, for example, her out-of-commuting zone friends or her work friends.[3]

In our empirical analysis, we want to study the effect of an individual's friends' house price experience on her housing investment behavior. Observing this investment behavior in the data presents a second measurement challenge. We overcome this challenge by introducing a second data set, which contains snapshots from Acxiom InfoBase for the years 2010 and 2012. These data are maintained by Acxiom, a leading marketing services and analytics company, and contain a wide range of individual-level information compiled from a large number of sources (e.g., public records, surveys, and warranty registrations). The data include information on demographics (e.g., age, marital status, education, occupation, income), household size, and homeownership status. For current homeowners, the data also include information on the housing transaction that led to the ongoing homeownership spell. This information includes transaction details from public deeds records (e.g., transaction date

[3]Our measure of friends' house price experiences treats each friendship link identically. We do not observe interactions between friends on Facebook that might allow us to infer differential tie strengths. Since we only observe one snapshot of the Facebook social graph, we also cannot exploit time-series variation in an individual's social network. $FriendHPExp^{N}_{i,t_1,t_2}$ thus measures the house price experiences between t_1 and t_2 of i's social network as of the date of snapshot, July 1, 2015. The interpretation of our empirical estimates thus requires that the counties an individual was exposed to in 2015 provide an unbiased estimate of the counties she was exposed to in the past.

and price), as well as property details from public assessor records (e.g., property size). We describe below how we use these data to measure various aspects of housing investment decisions.

We merge the Facebook and Acxiom data through a unique, anonymized link based on common characteristics in both data sets.[4] Since the public record housing transaction data is originally recorded at the county level, we will focus our empirical analysis on understanding the housing market behavior of the residents of Los Angeles County, the largest U.S. county by population. This ensures that our analysis is not affected by inconsistent recording of data across counties. Our final sample consists of an anonymized panel of about 1.4 million Facebook users who lived in Los Angeles County in 2010, and whom we can match across the 2010 and 2012 Acxiom snapshots.[5]

1.2 Descriptive Statistics

Table 1 shows summary statistics on characteristics of the individuals in our sample. For the average person we observe 304 total U.S.-based friends, of whom 125 live outside the Los Angeles commuting zone, which includes Los Angeles county as well as five surrounding counties (La Paz County, Orange County, Riverside County, San Bernadino County, and Ventura County). The number of total friends ranges from 35 at the 5$^{\text{th}}$ percentile of the distribution, to 943 at the 95$^{\text{th}}$ percentile of the distribution. Appendix Figure A1 shows the full distribution of friend counts across the individuals in our sample. In 2010, the average person in our sample was 41 years old, and had a household income of almost $70,000. About 48% of our sample was single in 2010, but 13% of those were married by the year 2012. The average household size in 2010 was 3. In 2010, 29.5% of the sample were renters; by 2012, 17.8% of these 2010 renters had transitioned to owning their home. Of the 70.5% of the population that owned their home in 2010, 93.5% continued to own their home in 2012.

In Section 3.1, we use these panel data to analyze how the transition probability between renting and owning across the two Acxiom snapshots is affected by the individuals' friends' house price experiences between 2008 and 2010, $FriendHPExp_{i,2008,2010}$. We call the associated regression sample the "change-of-tenure" sample. The average person in this sample has friends who experienced a 7.1% house price decline between December 2008 and December 2010. There is significant variation across individuals in their friends' average house price experiences over this horizon, consistent with significant variation in across-U.S. house price movements over this period (see Appendix Figure A2). Indeed, this number ranges between -10.1% at the 5$^{\text{th}}$ percentile of the distribution and -5.2% at the 95$^{\text{th}}$ percentile. The 5-95 percentile range of out-of-commuting zone friends' house price experiences is even larger, ranging from -16.3% to -5.2%. Panels A and B of Figure 1 plot the full distribution of friends' house price experiences separately for all friends and out-of-commuting zone friends.

In addition to analyzing the probability of individuals transitioning between renting and owning

[4]Linking the housing data to the friendship network was done exclusively for this research project, and involved a scrambled merge-key based on common characteristics. 53% of merges relied on email address. Other characteristics were full date of birth (51%) or year-month of date of birth (28%), last name (45%) and first name (84%), location at the level of zip code (44%), county (37%), and CBSA (8%), and telephone number (2%). Most matches are based on multiple characteristics.

[5]We drop the 17% of individuals with fewer than 10 out-of-commuting zone friends, for whom the measure of friends' geographically distant house price experience is noisy; however, our results are robust to variation in this cutoff.

across the 2010 and 2012 Acxiom snapshots, we want to investigate how other dimensions of their housing investment decisions are affected by their friends' house price experiences. To do this, we use the fact that we observe details of all transactions since 1993 that led to an ownership spell that was ongoing as of either Acxiom snapshot. Overall, we can match more than 520,000 of such housing transactions in Los Angeles county to the Facebook profile of the respective homebuyers. Appendix Figure A3 shows how these transactions are distributed across time; we observe at least 15,000 transactions every year. We will refer to this sample of transactions as the "transaction sample." In our empirical analysis in Sections 3.2 and 3.3, we will relate characteristics of these transactions, such as the size of the property purchased, to the house price experiences of the buyers' friends in the 24 months prior to the transactions.

Table 2 provides summary statistics on the transaction sample. The average transaction price was $403,340, and the average loan-to-value ratio at origination was about 85%.[6] The average property size was 1,775ft^2, and 77% of the purchased properties were single-family residences. We also present summary statistics on the buyers in these transactions.[7] The average homebuyer was 35 years old at the time of the transaction. For the average buyer, we observe 408 total Facebook friends, and 156 out-of-commuting zone friends. Panels C and D of Appendix Figure A1 show the full distribution of U.S.-based friends of those individuals purchasing a home. As before, we observe substantial variation in the house price experiences of the friends of buyers who purchased properties at the same time: after conditioning on the transaction quarter, the across-buyers standard deviation of $FriendHPExp_{i,t-24m,t}$ is about 3.5%. Panels C and D of Figure 1 show the full distributions of buyers' friends' house price experiences in the transaction sample, conditional on the quarter of the transaction.

These summary statistics highlight that, at any point in time, there is a substantial variation across different Los Angeles residents in the house price experiences of their friends. Much of this variation is driven by heterogeneity in the geographic dimension of different individuals' social networks, combined with heterogeneous house price movements across different parts of the United States. To better understand these sources of variation, we next explore various dimensions of the social networks of the individuals in our data.

1.3 Descriptive Statistics: Individual Networks

We first analyze the geographic spread of the social networks of the individuals in our matched Facebook-Acxiom sample of Los Angeles residents. Figure 2 plots the aggregated social networks of all individuals in this sample. Panel A shows a heatmap of the share of all friends that live in

[6] We observe transaction prices and mortgage amounts in ranges of about $50,000. We take the mid-point of the range as the transaction price and mortgage amount.

[7] For some of the transactions in the transaction sample, a property is purchased by more than one individual, and we can find both individuals on Facebook. In these cases, we average the set of characteristics, and pool the friends of the two buyers in our calculation of $FriendHPExp^N_{i,t_1,t_2}$. Only considering the characteristics and friends' house price experiences of the head of household yields very similar results. Observing multiple buyers for the same transaction is the main reason why we observe fewer observations in the transaction sample than we observe 2010 owners. The other reason is that some 2010 owners purchased their property prior to 1993, the first year in which detailed information on the purchases is available.

each county in the continental United States. A large fraction of the friendship links of Los Angeles residents are to other individuals living nearby. There are also significant friendship links to counties all along the West Coast. Other counties with sizable friendship links to Los Angeles are Maricopa County, AZ (Phoenix), Cook County, IL (Chicago), and Harris County, TX (Houston). More generally, we see significant exposure of Los Angeles residents to all major U.S. population centers. Similarly, as one might expect, the exposure of Los Angeles residents through their friends to sparsely populated areas is limited. Panel B presents a heatmap of the total number of friendship links of Los Angeles residents to each county, normalized by the number of Facebook users in that county. This figure captures the relative probability that a given Facebook user in a county will have a friend in Los Angeles. Relative magnitudes correspond to the relative probabilities of such friendship links. This relative probability is highest for individuals living in California and Arizona, and is generally declining in distance from Los Angeles. Among Facebook users living east of New Mexico, those that live in major population centers are more likely to have friends in Los Angeles than those living in more rural counties. Individuals living in Appalachia are least likely to have a friend in Los Angeles.

While Los Angeles residents are, on average, relatively well-connected to all major U.S. population centers, there is substantial heterogeneity in where different individuals have friends. Consider Figure 3, which maps the friendship networks of three different individuals in our sample (Appendix Figures A4 and A5 present additional examples). Panels A and B show the social networks for two individuals whose friends are clustered around Chicago and Oklahoma, respectively; Panel C presents the friendship network of an individual whose friends are more evenly distributed across U.S. population centers. To analyze this heterogeneity more systematically, Table 3 presents summary statistics across the individuals in our Los Angeles sample on the distribution of their U.S.-based friends. The average person in our sample has 62.9% of her friends within the Los Angeles commuting zone; 70.4% of the average person's friends live within California. Despite this relative clustering of friends near Los Angeles, the average person has friends in more than 55 different U.S. counties. We also measure the spread of social networks using geographic distance. The average person in our sample has 65.5% of her friends living within 200 miles of Los Angeles, and 79.1% living within 1,000 miles.[8] We confirm that there is substantial heterogeneity in the geographic dispersion of social networks across our sample. At the 5$^{\text{th}}$ percentile of the population distribution, individuals have friends in only 13 different counties, while at the 95$^{\text{th}}$ percentile, they have friends in more than 150 counties. Similarly, at the 5$^{\text{th}}$ percentile of the population distribution, individuals have 22.4% of their friends living in the Los Angeles commuting zone; at the 95$^{\text{th}}$ percentile, this number is 87.1%. Panel A of Figure 4 explores this heterogeneity further, and shows the various percentiles of the sample distribution of the share of friends living at distances spanning up to 1,000 miles.

We next explore which regional housing markets different individuals in our sample are exposed to through their friendship networks. Indeed, as suggested by the individual-level social networks in

[8] We assign friends to their county of residence, and use population-weighted county-centroids to assign geographic distances.

Figure 3, there is a substantial heterogeneity in this exposure that we exploit in our empirical analysis. For example, Table 3 shows that while the average person has about 32.4% of her out-of-commuting zone friends living in the Pacific census division (comprising Alaska, California, Hawaii, Oregon, and Washington), this number ranges from 5.7% to 66.7% between the 5th and the 95th percentile of the population distribution. As suggested by Figure 2, the second most common census divisions among the friends of the individuals in our sample is the Mountain division, comprising the states of Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, and Wyoming. On average, 20.1% of the out-of-commuting zone friends of the individuals in our sample live in the Mountain division, with a 5-95 percentile range of 2.5% to 48.5%. There is similar heterogeneity in the exposure to other U.S. census divisions. For example, while at the 5th percentile of the population distribution, individuals not have a single friend living in the South Atlantic census division (comprising Delaware, the District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, and West Virginia), at the 95th percentile of the distribution, individuals have almost a third of their out-of-commuting zone friends living in that division.

We next investigate the sources of heterogeneity in the geographic concentration of social networks across individuals. Panel A of Table 4 presents averages of network characteristics for various sub-groups in our sample. The geographic concentration of networks is declining in age. While individuals aged between 18 and 24 years have, on average, 75.3% of their friends living in the Los Angeles commuting zone, this number declines to about 54.5% for individuals over 65 years old. Panel B of Figure 4 shows that this pattern is consistent across all distances used to measure geographic concentration. The geographic concentration of social networks is also declining in education levels: while individuals with a high school degree have an average of 67.3% of their friends living within 200 miles, this number falls to 56.3% for individuals with a graduate degree (see Panel C of Figure 4).[9] More educated people do not only have fewer friends living near Los Angeles, they also have friends living in more unique counties. Lastly, it appears that females have slightly more geographically concentrated networks than males, but the differences are economically small (see Panel D of Figure 4).

Exposure to the different U.S. census divisions also differs by age and education. Appendix Figure A6 shows that while the share of out-of-commuting zone friends that live in the Pacific and Mountain division is decreasing in age, the share living in most of the other census divisions is increasing in age. The exception is the West South Central division (comprising Arkansas, Louisiana, Oklahoma, and Texas), which has a roughly constant share of friends across age groups. Appendix Figure A7 shows the exposure to different census divisions by education level. The share of friends in the Moutain division is decreasing in education, while the share of friends in the Middle Atlantic (New Jersey, New York, and Pennsylvania) and New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont) census divisions is increasing in education levels.

[9]While these numbers are produced for the full sample, the same patterns hold true within each age group. This statistic exploits a measure of the education level of individuals within the Facebook data – it is built, for example, on the fact that most individuals report their high school and college on their Facebook profile. The "Unknown" category comprises people for whom Facebook was unable to assign an education category.

While Panel A of Table 4 shows averages of network characteristics across demographic groups, Panel B explores how much of the variation in network characteristics can be explained by variation in these demographics. In particular, each entry reports the adjusted R^2 of an individual-level regression of the network characteristic presented in the column on dummy variables for each of the possible values of the demographic variable reported in the row. The age of the individuals appears to explain about 5% of the variation in the geographic spread of social networks, while education levels and gender can explain about 2% and 0.4% of the variation, respectively. Income and occupation, as measured in the Acxiom data, can each explain about 1% of the variation. The Los Angeles zip code in which the individuals live in 2010, which proxies for a variety of demographic characteristics of the individual, can explain about 8% of the variation in the geographic spread of networks. A subset of our sample report their hometown in their Facebook profile. Among those individuals, the identity of the hometown can explain between 30% and 40% of the geographic spread of their social networks. This suggests that a non-trivial amount of the variation in where individuals have friends is explained by where they grew up. Overall, these observable characteristics can jointly explain about 40% of the variation in the geographic spread of social networks across individuals.

Table 3 also highlights heterogeneity in social network characteristics other than geographic spread. For example, while the average person has 29.2% of friends in the age group 25 years to 34 years, at the 5^{th} percentile of the population distribution individuals have 4.6% of friends in that age group, while at the 95^{th} percentile this number is 75.5%. Similarly, while, for the average person, 18.9% of friends have only a high school degree, at the 95^{th} percentile of the population distribution, this figure is 36.5%.

Panel A of Table 4 shows that there is a strong correlation between the age of an individual and that of her friends. The average individual aged 18-24 has 68.6% of friends within that age group; on the other hand, individuals aged above 35 years have fewer than 7% of their friends aged between 18 and 24 years. The own-group age share is declining in age: individuals aged 35-44 have 44.8% of their friends in that age group, while individuals between the ages of 55 and 64 years have 29.2% of their friends in that age group. Panel B shows that own age explains between 50% to 70% of the variation of friend shares in the various age groups. Similarly, we find that, on average, individuals are more likely to be friends with others that have similar education levels. For example, while only 6.4% of all friends of people with only a high school degree went to graduate school, this number is almost 25% among individuals that themselves went to graduate school. Indeed, the own education levels explains more than a quarter of the variation in the share of friends that have a graduate degree, and more than 15% of the variation in the share of friends that only have a high school degree. Interestingly, hometown and zip code of current residence can also explain a significant proportion of the variation in the share of friends with various educational levels.

1.4 Social Networks: Los Angeles vs. Rest of United States

While our individual-level analysis of the role of social networks in the housing market focuses on Los Angeles residents, we next consider how representative those individuals' networks are for the rest of the United States. This is important when considering whether one might expect to find similar effects of social networks on housing market outcomes in other regions.

Table 5 shows the summary statistics of key network statistics across U.S. counties. Recall that the median person in our sample had 70.9% of her friends living within 200 miles. This number is relatively representative of the rest of the United States. Indeed, the median person in the (population-weighted) average county has 72.8% of friends living within 200 miles. There is substantial heterogeneity across counties in the share of friends that live within 200 miles; Appendix Figures A8 and A9 provide examples showing the geographic distribution of social networks for six counties. At the 5th percentile of the population-weighted county distribution, the median person in a county has 54.5% of friends living within 200 miles; at the 95th percentile, this number is 84.7%. Panel A of Figure 5 plots the share of friends living within 200 miles for the median person living in each county in the continental United States. Social networks are most geographically concentrated in the South and Midwest. In fact, the 12 counties with the most concentrated networks are all in Kentucky – the median person in each of these counties has more than 90% of her friends living within 200 miles. On the other hand, social networks in the sparsely-populated parts of the non-coastal western United States are the least geographically concentrated. The exception is Utah, which has fairly geographically concentrated social networks even in the low-population-density areas outside of Salt Lake City. Conversely, the densely-populated coastal regions of Florida appear to have relatively dispersed social networks.

We next analyze the extent to which the geographic concentration of the county-level social networks depends on county-level demographics. Panels B and C of Figure 5 show the relationship between the share of friends of the median person in a county that lives within 200 miles, and two county-level demographic measures from the 2010 5-year wave of the American Community Survey: the share of individuals with at most a high school degree, and the median household income. Counties with higher education levels and higher incomes have less geographically concentrated friendship networks, mirroring the individual-level patterns uncovered in the previous section.

Much of the variation in friends' house price experiences that we exploit in this paper comes from differences in the geographic spread of social networks among individuals living in the same county. Indeed, the inter-quartile range of the share of friends living within 200 miles across the individuals in our sample is 25.9%. Table 5 shows the across-county distribution of the within-county inter-quartile range of the share of residents' friends living within 200 miles. For the average county, this inter-quartile range is 30.1%, but it ranges from about 15% at the 5th percentile of the county distribution to almost 50% at the 95th percentile. This shows that counties differ in how similar the social networks of its residents are to each other. However, even for counties with relatively homogeneous social networks, there is substantial heterogeneity in the networks' geographic dispersion across the population. This suggests that differences in social network house price experiences might induce substantial variation in housing market expectations and investments across individuals in local housing markets across the United States.

2 Empirical Strategy

In the previous section, we described how we combine a number of new data sets to measure both the house price experiences of different individuals' friends, as well as those individuals' housing market investments. In this section, we describe our empirical approach for identifying the causal effect of the house price experiences within an individual's social network on her housing market behavior.

Our baseline specifications in Section 3 are regressions of outcome variables at time t_2, such as the size of the property purchased, on measures of the house price experiences within that buyer's social networks between t_1 and t_2, and control variables:

$$Outcome_{i,t_2} = \beta FriendHPExp^{N}_{i,t_1,t_2} + \gamma \mathbf{X}_{i,t_2} + \psi_{t_2} + \epsilon_{i,t_2} \tag{2}$$

The key explanatory variable, $FriendHPExp^{N}_{i,t_1,t_2}$, is constructed as described in the previous section (see equation 1). In order to interpret estimates of β in regression 2 as the causal effect of friends' house price experiences, we need to rule out potential alternative, non-causal channels that might also induce a correlation between a person's housing market investments and her friends' house price experiences.

A first concern is that $FriendHPExp$ might be correlated with an individual's own house price experiences or her own past capital gains, both of which could directly affect her housing investment decisions. In particular, since most people have many local friends, shocks to Los Angeles house prices are likely to shift $FriendHPExp$, and more so for people with a larger share of friends in Los Angeles. Since our sample is restricted to Los Angeles residents, any direct effect of past Los Angeles house prices that is equal across Los Angeles residents is absorbed by time fixed effects, ψ_{t_2}. However, any confounding effect of past Los Angeles house price movements that was stronger for people with a larger share of friends in Los Angeles would alter our interpretation of β. For example, suppose that people who have lived in Los Angeles for longer both have more friends in Los Angeles, and are more likely to directly extrapolate from Los Angeles house prices when forming their expectations about future house price growth. This could induce a correlation between a person's housing market investments and $FriendHPExp$ that is not due to social interactions. Similarly, imagine that a person who has lived in Los Angeles for longer is more likely to already own a house in Los Angeles. In that case, higher Los Angeles house price growth can have a stronger effect on this person's housing market investments both because her larger local network has experienced bigger house price increases, and because she has larger past capital gains on her existing home. If we cannot control for such past capital gains in $\mathbf{X}_{i,t_2}$, we would erroneously attribute all observed effects to social interactions.

To address this challenge, we estimate regression 2 using an instrumental variables (IV) strategy, where we instrument for the house price experiences of all of individual i's friends, $FriendHPExp^{All}_{i,t_1,t_2}$, with the house price experiences of her friends living outside of the Los Angeles commuting zone, $FriendHPExp^{OutCZ}_{i,t_1,t_2}$. The first and second stages of this IV regression, respectively, are given by:

$$FriendHPExp^{All}_{i,t_1,t_2} = \beta^{FS} FriendHPExp^{OutCZ}_{i,t_1,t_2} + \delta \mathbf{X}_{i,t_2} + \xi_{t_2} + \varepsilon_{i,t_2} \tag{3}$$

$$Outcome_{i,t_2} = \beta^{IV} \widehat{FriendHPExp}^{All}_{i,t_1,t_2} + \gamma \mathbf{X}_{i,t_2} + \psi_{t_2} + \epsilon_{i,t_2} \tag{4}$$

The instrument has a very high F-statistic in the first-stage regression 3. This is because the construction of the instrumented variable directly builds on the instrument:

$$FriendHPExp^{All}_{i,t_1,t_2} = ShareFriendsLA_i \times \Delta HP_{LA,t_1,t_2} + (1 - ShareFriendsLA_i) \times FriendHPExp^{OutCZ}_{i,t_1,t_2}.$$

Indeed, if all individuals had the same share of friends in Los Angeles, the first stage of our instrumental variables regression would have an R^2 of 1. The second stage of the IV, regression 4, includes a predicted $\widehat{FriendHPExp}^{All}_{i,t_1,t_2}$ that can be thought of as generated under the assumption that all individuals have the same share of their friends living in Los Angeles. Our estimates of β are therefore only identified by variation in $FriendHPExp^{All}_{i,t_1,t_2}$ that is independent of individual-specific variation in the share of Los Angeles-based friends. We can thus rule out concerns that our estimates are confounded by any mechanism that would induce individuals with a higher friend-share in Los Angeles to react more to past Los Angeles house price movements for reasons other than social interactions.[10]

Even with this IV approach, a further concern relates to people who recently moved to Los Angeles from parts of the country where they have many friends. For these people, there might be a strong correlation between their own house price experiences and capital gains, and the house price experience of their friends that live outside of the Los Angeles commuting zone. To rule out such concerns, we verify that our results are robust to excluding recent movers to Los Angeles from our regressions.

We also consider whether the non-random variation in individuals' geographically distant social networks documented in Section 1.3 poses a challenge to our causal interpretation of β in regression 2. A first important observation is that our identification does not require that individuals' social networks do not systematically vary with those individuals' observed and unobserved characteristics.

[10]We choose to interpret estimates from the IV regression 4, rather than from the reduced form regression that directly includes $FriendHPExp^{OutCZ}_{i,t_1,t_2}$ in regression 2. This is because we find the interpretation of the magnitude of the IV estimates to be more natural. If we instead ran the reduced form specification, the magnitude of β will be similar to the magnitude of β^{IV} scaled by the average share of out-of-commuting zone friends. These reduced form estimates would capture the average effect of the house price experiences of only the out-of-commuting zone friends on the outcome of interest. One assumption in our interpretation of the IV estimates is that the effect of friends' house price experiences on own housing investment, through social interactions, is similar for geographically close and distant friends. There is some evidence that this is indeed a valid assumption. Appendix Table A5 shows that our results do not depend on whether we use out-of-commuting zone friends or out-of-state friends' experiences as the instrument, suggesting that households respond similarly to the experiences of friends in neighboring commuting zones relative to the experiences of friends that are further away. However, if one were instead to expect a larger social-interactions-induced reaction to the experiences of geographically close friends, the magnitude of β^{IV} would understate the effect of the response to the house price experiences of all friends.

For example, it is not necessarily a problem that people with graduate degrees are more likely to have friends in New England, and are more likely to buy a house. This is because our dependent variable is driven by where in the U.S. people have friends, *interacted with* how house prices in these areas change in a given year. Since house price growth in New England is sometimes above and sometimes below the U.S. average, the same individual's social network will sometimes experience above-average and sometimes below-average house price changes.[11] By comparing the housing investment behavior of individuals with friends in New England across different years, we can thus remove the effect of any time-invariant individual-level determinant of housing investments that is also correlated with having friends in New England.

Indeed, we find that there are no social networks that consistently experience above-average or below-average house price appreciation over extended periods of time. To document this, we calculate, for each individual in our sample and year between 1993 and 2012, the house price experiences in that individual's social network over the previous 12 months. We then regress these individual-year observations on individual fixed effects. This regression yields an R^2 of about 0.1%. This shows that, on average, the variation in the house price experiences across different individuals' friends is unrelated to observed or unobserved characteristics of those individuals. Consistent with this, our estimates are unchanged in those empirical specifications where we can include buyer fixed effects, and thus exploit only within-individual across-time variation in friends' house price experiences.

A second, more subtle concern with our causal interpretation, is that shocks to an individual's desire or ability to buy a house *in a given year* might vary systematically with the house price movements *in that year* in those geographically distant areas where this individual has friends. This challenge is weaker than that faced by the peer effects literature, which has to address concerns about common unobserved shocks to individuals and their friends. For example, in our setting it is not problematic that people and their friends have children around similar times, and therefore also buy houses around similar times. This is because $FriendHPExp$ does not depend on the housing market *decisions* of an individual's friends. Instead, it is only driven by the house price changes in the counties where those friends live. Therefore, challenges to our identification have to come from shocks that not only affect an individual's own housing market decisions, but that also move equilibrium house prices in geographically distant counties where that individual has friends.

Along those lines, we were able to identify and address one potential challenge to our interpretation coming from individuals that work in professions or industries that feature significant geographic clustering. Suppose that people who work in the tech sector have more friends in Silicon Valley. During tech booms, tech employees in Los Angeles might have more resources to buy a house, and the increase in housing demand by the many tech employees in Silicon Valley drives up house prices there. Without controlling for *year* $\times$ *tech sector* fixed effects, one might falsely attribute large housing investments by Los Angeles-based tech employees in those years to social interactions. We address

[11] In that sense, we exploit a variation similar to Bartik-instruments regularly employed in public finance (see Conley and Udry, 2010, for a study of social networks using a similar strategy).

challenges along these lines using three complementary strategies. First, we estimate specifications that include year-specific controls for a rich set of observable individual characteristics. These interacted controls have no effect on our estimates of β, suggesting that year-specific shocks to different demographic groups that correlate with house-price changes in their geographically distant social networks are not driving our results. Second, we show that our results are robust to focusing on the sample of buyers who are retired or work in geographically non-clustered professions (e.g., teachers and legal professionals). Third, to further address concerns about possible confounding effects from income shocks to connected counties, we present specifications that control for friend-weighted income changes over the past 24 months. This measure is constructed similarly to equation 1, where $\Delta HP_{c,t_1,t_2}$ is replaced by $\Delta Inc_{c,t_1,t_2}$. Income is measured as the gross income per capita from the IRS Tax Statistics SOI. We show that this additional control does not affect our estimated response of housing investment behavior to friends' house price changes. Jointly, these robustness checks suggest that our estimates are not driven by changes to the economic conditions of an individual's friends, which may correlate with both this individual's own behavior and her friends' house price experiences.

3 Friends' House Price Experiences and Housing Investments

In this section, we use the empirical strategy described above to document that the house price experiences within individuals' social networks have a causal effect on these individuals' housing investment decisions. We first analyze the extensive margin of housing investment. We document that individuals whose friends experienced larger recent house price increases are more likely to transition from renting to owning, and less likely to transition from owning to renting. Section 3.2 shows that the intensive margin of an individual's housing investment – the square footage of the home bought – also responds positively to higher house price experiences in the individual's social network. Section 3.3 documents that individuals whose friends experienced more positive house price movements are willing to pay more for a given home. More positive house price experiences of the sellers' friends are also associated with higher transaction prices.

3.1 Extensive Margin of Housing Investment

We first analyze the effect of friends' house price experiences on the extensive margin of the housing investment choice, that is, the decision to be a homeowner or a renter. To measure changes in homeownership status, we need to observe a panel of individuals across at least two points in time. As described in Section 1, we observe the homeownership status of a panel of individuals in both 2010 and 2012. This allows us to analyze the effect of friends' house price experiences on the decision to buy and sell a house between these two dates. We do not have the data that would allow us to observe ownership transitions over other time windows.

We begin by focusing on the more than 430,000 Los Angeles-based renters in 2010 in the change-of-tenure data set.[12] Regression 5 considers whether their propensity to become a homeowner by 2012

[12] Appendix Table A1 presents summary statistics on the change-of-tenure sample by 2010 homeownership status.

is affected by the house price experiences of their friends between 2008 and 2010.

$$\mathbb{1}_{Owner_{i,2012}} = \alpha + \beta FriendHPExp^{All}_{i,2008,2010} + \gamma \mathbf{X}_{i,2010} + \omega \Delta \mathbf{X}_{i,2010,2012} + \psi_{zip_{2010},zip_{2012}} + \epsilon_i \tag{5}$$

The dependent variable is an indicator of whether individual i is a homeowner in 2012. We control for paired 2010×2012 zip code fixed effects (e.g., an indicator variable for all individuals that lived in zip code 90001 in 2010 and in zip code 90005 in 2012), which allows us to isolate the decision of where to live from the decision of whether to buy a house. We also control for the 2010 demographics of individual i, $\mathbf{X}_{i,2010}$, and changes in these demographics between 2010 and 2012, $\Delta\mathbf{X}_{i,2010,2012}$. Our controls also include information on the size of the individuals' Facebook networks, such as the number of friends, the number of out-of-commuting zone friends, and the number of counties in which they have at least one friend. As described in Section 2, to help us isolate the causal effect of friends' house price experiences, we use the house price experiences of friends who live outside the Los Angeles commuting zone to instrument for the house price experiences of all friends.

Panel A of Table 6 shows results from regression 5, with standard errors clustered at the zip_{2010}-level. On average, 17.8% of 2010 renters own a home by 2012. The estimate of β suggests that every percentage point increase in the house price experiences of an individual's friends increases her probability of becoming a homeowner by 2012 by about 0.6 percentage points. A one-standard-deviation increase in the house price appreciation experienced by a person's friend between 2008 and 2010 increases the probability of buying a home over the next two years by 1.2 percentage points.

Throughout our analysis, we control for demographic characteristics of the individuals. We deal with missing characteristics in two ways. In column 1 and most other specifications, we replace missing characteristics with their own fixed effects. This approach allows us to use the full data in the estimation of β, but is potentially problematic if missing characteristics occur non-randomly in a way that is correlated with $FriendHPExp$. In column 2, we thus focus only on those individuals for which we observe a complete set of control variables. The point estimates of β are similar in both cases.

Appendix Table A2 shows the coefficients on the control variables for the estimates in column 1 of Table 6. Larger households, growing households, households with higher income, and households with higher income growth are all more likely to transition from renting to owning. In addition to documenting the quality of our demographic controls, these estimates allow us to compare the effect size of friends' house price experiences to important life-cycle factors. For example, we find that for renters, a 10 percentage point higher house price experience in their social network (a 5.2 standard deviation move over this period), has a similar effect on the probability of buying a house as the addition of a family member. In other words, large shifts in friends' house price experiences have effects on housing investments that are of similar magnitude as life-cycle motives.

While the $\psi_{zip_{2010},zip_{2012}}$ fixed effects help us to separate the choice of location from the choice of owning or renting, in column 3 we restrict our analysis to individuals that lived in the same zip code in 2010 and 2012, i.e., to people for whom moving to a different part of Los Angeles is not a driver of ownership change. The average probability of transitioning from renting to owning is lower in this sample, at 10.3%. The estimated effect of friends' house price experiences on the probability of buying a home is only marginally smaller than in the full-sample.

As discussed in Section 2, the specifications in columns 4 and 5 of Table 6 address concerns that our results could be driven by common shocks to individuals and her friends that might be large enough to move aggregate house prices in those geographically distant regions where these friends live. Column 4 only exploits variation in friends' house price experiences among individuals who are either retired or who work in geographically non-clustered professions. The estimated effect of friends' house price experiences is only marginally smaller in this specification.[13] In column 5, we directly control for recent average income changes in the individuals' social networks. Income changes in a person's social network do appear to also be correlated with that person's housing market investments: a one percentage point higher income growth among a renter's friends is associated with a 0.33 percentage point higher probability of buying a house over the next two years. This could, for example, be picking up an effect of people working in professions that are disproportionately prevalent in counties where they have friends. Importantly for us, the estimated effect of friends' house price experiences on the purchasing decision remains nearly unchanged.[14] These findings provide evidence against the argument that our findings are driven by unobserved income shocks.

So far, we have focused on the effects of friends' house price experiences between 2008 and 2010 on a 2010 renter's decision of whether to buy a house by 2012. However, friends' house price experiences between 2010 and 2012 might also affect the decision to buy a house by 2012. In column 6, we therefore present results from a regression that also includes friends' house price experiences between 2010 and 2012, in addition to the experiences of these friends between 2008 and 2010. A one percentage point higher house price appreciation by an individual's friends between 2010 and 2012 indeed further increases the likelihood of that individual becoming a homeowner by 2012 by about 0.32 percentage points. The effect of friends' house price experiences between 2008 and 2010 is unaffected.

Panel A of Table 6 focuses on the housing investment behavior of 2010 renters. In Panel B, we instead focus on the behavior of 2010 homeowners, and analyze how their friends' house price experiences affect the probability that they sell their home by 2012. Only about 6% of 2010 homeowners become renters by 2012. The results, which closely mirror those in Panel A, suggest that homeowners

[13] In this specification, we add an indicator that is equal to 1 for all professions not identified as geographically non-clustered, and set $FriendHPExp$ equal to zero for these individuals. This allows us to only exploit variation in $FriendHPExp$ coming from individuals in geographically non-clustered professions while using the full sample to estimate the effect of the control variables and fixed effects.

[14] The correlation of house price growth and income growth between 2008 and 2010 across the social networks in our sample is 37%. This suggests that there is substantial variation that allows us to separately identify the effect of house price changes and income changes in the geographies where an individual has friends. Where is this variation coming from? One indication is to look at the relative exposure to various census regions of individuals with different combinations of house price growth and income growth among their friends. We find that individuals whose friends experienced both relatively low income growth and relatively high house price growth (i.e., a relatively smaller house price decline) between 2008 and 2010 have disproportionately many friends in the East North Central and West North Central census divisions. Conversely, friends that experienced relatively larger house price declines but relatively higher relative income growth live disproportionately in the Mountain and Mid Atlantic census divisions.

whose friends experienced particularly large house price declines are more likely to sell their house. For 2010 homeowners, the magnitude of the effect of friends' house price experiences on the probability of owning a home in 2012 is a quarter to a third of the size of the effect as it is for 2010 renters.

3.2 Intensive Margin of Housing Investment

We next analyze whether, conditional on buying a house, the house price experiences of a buyer's friends affect the intensive margin of her property investment. The unit of observation in regression 6 is a property purchase of individual i at time t. As discussed in Section 1.2, this includes all property transactions since 1993 that led to ownership spells that were still ongoing as of either 2010 or 2012. The dependent variable is the log square footage of the purchased property, multiplied by 100 to facilitate interpretation of the coefficients. The key explanatory variable, $FriendHPExp^{All}_{i,t-24m,t}$ is constructed as in equation 1, and captures the average house price changes experienced by buyer i's friends in the 24 months prior to the purchase.

$$log(PropSize_{i,t}) = \alpha + \beta FriendHPExp^{All}_{i,t-24m,t} + \gamma \mathbf{X}_{i,2010} + \psi_t + \epsilon_{i,t} \quad (6)$$

In column 1 of Table 7, we control for purchase-month fixed effects, ψ_t, and buyer characteristics, $\mathbf{X}_{i,2010}$.[15] The estimates suggest that a 5 percentage point (1.4 within-quarter standard deviations) increase in friends' average house price experiences is correlated with buyers purchasing a 1.6% larger property. This documents that buyers increase their portfolio share in housing when their friends have experienced larger recent house price increases. To put the magnitude of the effect into perspective, conditional on other control variables, those households that in 2010 had an income between $75,000 and $99,999 bought properties that were about 9.7% larger than the properties bought by households that had an income between $50,000 and $74,999.

When individuals choose to purchase larger properties, they can either purchase a larger house in the same neighborhood or move to a different neighborhood where larger properties are available. In column 2 of Table 7, we add zip code fixed effects to measure the relative importance of these two factors. The estimate of β drops by about 20%, suggesting that most of the adjustment involves buying a larger property in a given area.

Columns 3 to 7 address a number of potential concerns with our causal interpretation of the estimates of β in regression 6. As discussed in Section 1, for property purchases before 2010, we only observe information on the transaction if the property does not get resold prior to 2010. If the probability of a fast resale was correlated with both house price experiences of the buyers' friends and the size of the house bought, this selection could bias our results. In column 3, we therefore focus on sales since 2010, for which we observe a non-selected sample. The point estimate of β in this sample is

[15] We observe buyer age at the time of the transaction, but for other buyer characteristics, such as occupation, marital status, and household size, we use values from the most proximate Acxiom snapshot. While the coefficients on the individual household characteristics are not the direct object of interest in this paper, Appendix Table A3 shows the coefficients on these characteristics. Richer and older people generally purchase larger properties. Larger households purchase larger properties, and married individuals buy larger properties than single individuals.

slightly larger than the point estimate in the full sample, though the two estimates are not statistically distinguishable. This suggests that the selection of our transaction sample does not bias the results.

A second concern with our causal interpretation was that even though we only exploit variation in the house price experiences of friends living outside of Los Angeles, for buyers who move from these regions to Los Angeles, their own experiences and capital gains might still be correlated with the experiences of those friends (see Section 2). To test whether this confounds our estimates, column 4 further restricts the sample to purchases since 2010 for which we can verify that the buyer lived in Los Angeles in 2010. The effects are nearly identical to those in the sample of all purchases since 2010. Housing wealth effects or an extrapolation of own house price experiences thus cannot explain our findings.

As discussed in Section 2, an additional challenge to our causal interpretation of β comes from characteristics of the buyer that might have a particularly strong direct effect on property investments in years when the buyers' geographically distant friends experience particularly high house price increases. In column 5, we limit the scope of such possible confounding effects by interacting buyer characteristics with purchase-year fixed effects. In column 6, we only exploit variation in $FriendHPExp$ among buyers that are retired or that work in geographically non-clustered professions. Column 7 includes direct controls for income changes in the buyers' social networks. Across these specifications, the estimates of β are similar to our baseline estimates in column 1, indicating that common shocks to individuals and their social networks do not explain the observed effect of friends' house price experiences.

3.3 Transaction Price

So far, we have documented that the house price experiences within individuals' social networks affect the extensive and intensive margins of their property investment decisions. In this section, we analyze the effects of the house price experiences of both the buyers' friends and the sellers' friends on transaction prices. Conceptually, the property valuations of both buyers and sellers would be affected by their friends' house price experiences. In any bargaining model, the final transaction prices will then vary with these valuations (Wheaton, 1990; Piazzesi, Schneider, and Stroebel, 2015).

For this analysis, we again consider the transaction sample, and run hedonic regression 7. The unit of observation is a transaction of house h, bought by individual i, at time t. The dependent variable is the log of the transaction price, multiplied by 100 to facilitate the interpretation of the coefficients. All specifications include zip code by transaction year fixed effects, $\phi_{zip} \times \psi_{y(t)}$. We also control for buyer characteristics, $\mathbf{X}_{i,2010}$, and for property characteristics, $\mathbf{Z}_h$.

$$log(Price_{h,i,t}) = \alpha + \beta FriendHPExp^{All}_{i,t-24m,t} + \delta \mathbf{X}_{i,2010} + \gamma \mathbf{Z}_h + \phi_{zip} \times \psi_{y(t)} + \epsilon_{h,i,t} \quad (7)$$

Panel A of Table 8 presents the main results of regression 7. The estimate in column 1 suggests that when homebuyers' friends experience a 5 percentage point higher house price appreciation, the transaction price for a given home is 2.3% higher.[16] To put this magnitude into perspective, it approximately corresponds to the price difference between an 1,140 square foot property and a 1,200 square foot property. The R^2 of the regression is over 80%, confirming that our hedonic property characteristics capture many of the important determinants of house prices.

While the hedonic regression controls for many determinants of property value, one might be concerned that individuals with larger house price increases in their social networks purchase properties that differ on unobservable characteristics, which could bias the estimates of β in regression 7. To rule out such confounding effects, column 2 includes property fixed effects in the regression. In this specification, β is only identified by transactions of properties for which we observe two transactions.[17] Since we are comparing transaction prices for the same property, this specification holds constant all unobservable characteristics of the properties. Overall, we observe 34,732 transactions for properties that trade twice in our sample. As one would expect, including property fixed effects increases the R^2 further, to well over 90%. Reassuringly, the effect of positive house price experiences among a buyer's friends on the transaction price is unaffected.[18]

As discussed in Section 2, one concern with our causal interpretation of these results is that friends' house price experiences might be correlated with unobserved buyer characteristics that could have a direct effect on her housing investment decisions. We argued that this was unlikely, since our identification comes from the *interaction* of the geographic spread of an individual's friends and the time-varying house price movements in those counties. To highlight this source of identification, column 3 includes buyer fixed effects. In this specification, all identification comes from individuals that we observe purchasing more than one property.[19] Across those transactions, the friendship networks and unobservable characteristics of the buyers are held fixed, and the only force shifting $FriendHPExp$ across the transactions is the house price development in the same individuals' friendship networks across the two periods in which the individuals bought a house. Our estimate of β is very similar in this specification, highlighting that our results are not confounded by the correlation between individuals' demographic characteristics and the geographic distribution of their social networks.

So far, we focused on the effect of the house price experiences of the buyers' friends on the sales price. In columns 4 and 5 of Table 8, we include the house price experiences of the sellers' friends in the 24 months before the sale as an additional regressor.[20] When sellers' friends experience a 5

[16] While the coefficients on the individual property and buyer characteristics are not our object of interest, Appendix Table A4 shows these coefficients. For example, larger properties and single family residences trade at a premium.

[17] In order to identify such repeat sales of the same property, one of the transactions has to occur before 2010, and the other between 2010 and 2012, so that we see the property attached to a different owner across the two Acxiom snapshots.

[18] In addition, one might worry that some of these properties were "flipped" and upgraded between the two transactions that we observe. However, the results are identical if we restrict the repeat sales sample to transactions that are more than five years apart or more than ten years apart.

[19] In order to identify two transactions by the same buyer, we need the same individual to owner-occupy two different properties in the 2010 and 2012 Acxiom snapshots. This will then allow us to observe information about the transaction that initiated each ownership spell.

[20] We can only observe information on the seller for transactions between 2010 and 2012, since for those transactions we know who lived in the property in 2010, prior to it being sold. We can match the sellers in about 20,000 transactions to their Facebook accounts. We include all transactions in the regression, even if we cannot match the seller to Facebook, in

percentage point higher house price appreciation, the transaction price is 1.2% higher. The estimated effect of the buyers' friends' house price experiences is similar to our baseline estimates. This evidence is consistent with friends' house price experiences affecting both the buyers' and the sellers' valuations of the property, and therefore their reservation prices in the bargaining that determines the final sales price.[21]

In Panel B of Table 8, we address a number of challenges to our identification. In column 1 we address concerns related to a potential selection of our transaction sample, in column 2 we remove buyers who previously lived outside of Los Angeles, and in columns 3-5 we address concerns about the effects of correlated shocks to individuals and her friends that can move house prices in geographically distant regions where this person has friends. As was the case in our analysis of the intensive margin decision, we find no evidence for any of these concerns.

3.4 Robustness Checks and Differential Effects

In Appendix Table A5 we present a number of robustness checks to our main results. First, in Panel A, we show that results are extremely similar when we use the house price experiences of out-of-state friends as an instrument, instead of the house price experiences of out-of-commuting zone friends. This alleviates concerns that our results could be driven by friends living just outside of the Los Angeles commuting zone in areas with house prices that are highly correlated with those in Los Angeles.

In our baseline specification, we consider the effect of friends' house price experiences over the previous 24 months. We also analyze whether the effects change when we consider other time horizons over which we measure friends' house price experiences. Specifically, in Panels B to D of Table A5, we use friends' house price experiences over the prior 12 months, 36 months, and 48 months as explanatory variables. We find that the magnitude of the effect is declining as we increase the time window over which we measure friends' house price experiences. This suggests that the most recent experiences within a person's social network have the largest effects on her behavior.

In addition, we analyze a number of sample splits to consider whether effects differ across the population. One interesting question is whether the effects are stronger or more muted for first-time homebuyers relative to repeat homebuyers who have more experience in the housing market. While we do not observe previous homeownership status for most buyers in the transaction sample, we do observe the age of the individuals. In Appendix Table A6, we thus analyze the effects separately for individuals in different age groups. Columns 1 and 2 show that the effect of friends' experiences on the probability of buying a house for renters, or selling a house for owners, are declining in the age of the individuals. Columns 3 and 4, on the other hand, show stable effects across age groups on the

order to increase statistical power in estimating the coefficients on the property characteristics and the buyer experience. In particular, in that specification, we also include an indicator, $FBMiss_i$, that is equal to 1 for all transactions where we cannot match the seller to their Facebook profile, and 0 otherwise. We set $FriendHPExp$ equal to zero when $FBMiss_i = 1$. However, estimates are similar if we only focus on the transactions for which we can identify both the buyer and the seller.

[21] We find that, on average, buyers' friends have 31 basis points less negative house price experiences over the two years before the purchase than sellers' friends (-3.47% vs. -3.78%). Equality of the means is rejected with a t-statistic of 6.39 (p-value = 0.000).

size of the property purchased, and the price paid for a given property. Relatedly, in Appendix Table A7, we show that there are no systematic differences in the effect size across individuals with different education levels.

We also consider whether the response of individuals' housing investment behavior to their friends' house price experiences is different during periods with booming housing markets relative to periods with more stable or declining housing markets. In Appendix Table A8, we split the analysis of the effect of friends' house price experiences on the size bought and the price paid into three periods: the housing boom period between 2001 and 2006, the housing bust period between 2007 and 2009, and the relatively flat period between 2010 and 2012. As discussed above, we can only analyze the effect on ownership transition probabilities between 2010 and 2012, precluding us from an analysis of this outcome across various stages of the housing cycle.[22] The effect on the price paid is nearly identical across these three periods. The effect on size bought is somewhat larger in the boom and flat periods than in the housing bust period. These findings suggest that the social dynamics channel we document in this paper is likely to be active both during housing booms and busts.

4 Investigating Mechanisms

In the previous section, we documented a causal relationship between the house price experiences in an individual's social network, and her housing investment behavior. In this section, we investigate possible explanations for causal relationship. We first provide evidence for a mechanism that works through affecting people's perceptions of the attractiveness of property investments. We also explore why individuals might adjust their perceptions about the attractiveness of housing investments in response to house price movements in geographically distant areas where they have friends. We then consider three additional potential causal mechanisms through which the house price movements in a person's social network could influence her housing market expectations, but do not find evidence for any of them. We conclude that the data are most consistent with a story in which the house price experiences of an individual's geographically distant friends, through social interactions, affect her housing market beliefs, and through this channel her housing investment behavior.

4.1 Evidence for Expectations Channel

A first plausible channel through which the house price experiences in a person's social network can affect her housing market investments is through influencing her perceptions of the attractiveness of property investments. A number of possible mechanisms for such an expectations-based channel have been proposed in the literature, though little systematic empirical evidence has been developed.

One important dimension along which existing theories differ is whether agents are mechanically influenced by signals they receive through their networks, or whether they attempt to rationally infer some true state of the world from the experiences of their friends (see Golub and Sadler, 2015, for a

[22] However, note that the house price experiences between 2008 and 2010, when the across-individuals average house price experience of their friends was -7.1%, influenced this probability in a similar way as the house price experiences between 2010 and 2012, when the average person's friends experienced a house price gain of about 4.3%.

review of the social learning literature). For example, one prominent narrative of the role of social interactions in the housing market has been put forward by Shiller (2007), who writes that "many people seem to be accepting that the recent home price experience is at least in part the result of a social epidemic of optimism for real estate." Shiller (2008) described "the contagious optimism, seeming impervious to facts, that often takes hold when prices are rising [...] speculative bubbles are fueled by the social contagion of boom thinking. [...] Like booms, many busts are magnified by group thinking." In Shiller's story, individuals are mechanically "infected" by the optimism and pessimism of their friends, which in turn are driven by their friends' own house price experiences through an extrapolation of own past experiences. This response to the optimism or pessimism of your friends is independent of whether the house price experiences of those friends contain useful information for predicting future Los Angeles house prices.

We next document that social interactions indeed have important effects on individuals' perceptions of the attractiveness of housing market investments. We also attempt, to the extent possible, to understand whether our findings are more consistent with a mechanical or a rational response to friends' house price experiences.

4.1.1 Description of Expectations Survey

Investigating the response of an individuals' expectations to her friends' house price experiences presents an additional challenge: how do we measure those expectations? To overcome this measurement challenge, we analyze responses to a short user survey conducted by Facebook in November 2015. The survey targeted Facebook users living in a few Los Angeles zip codes through a post on their News Feed.[23] It informed users that "Facebook is helping researchers understand what real people think about the economy. Your survey responses will be combined with the information that you publicly share on Facebook and average house prices to better help us understand the housing economy. Help us out by answering the following questions, your responses will be kept anonymous," followed by four multiple-choice questions.

1. *How informed are you about house prices in your zip code?*

   [x] Not at all informed   [x] Somewhat informed   [x] Well informed   [x] Very well informed

2. *How informed are you about house prices where your friends live?*

   [x] Not at all informed   [x] Somewhat informed   [x] Well informed   [x] Very well informed

3. *How often do you talk to your friends about whether buying a house is a good investment?*

   [x] Never   [x] Rarely   [x] Sometimes   [x] Often

[23] A person's News Feed is a personalized, constantly-updating list of content posted by friends and followed pages (e.g., messages, photos, videos), advertisements, and surveys. It is shown to users as the landing page when they log onto Facebook. Appendix Figure A11 shows a screenshot of the survey interface in a user's News Feed.

4. *If someone had a large sum of money that they wanted to invest, would you say that relative to other possible financial investments, buying property in your zip code today is:*[24]

   [x] A very good investment [x] A somewhat good investment [x] Neither good nor bad as an investment [x] A somewhat bad investment [x] A very bad investment

We observe 1,242 survey responses. 55% of respondents are male. The respondents' age ranges between 19 years and 75 years, with an average of 46 years, and an interquartile range of 35 - 56 years. Respondents are spread over 113 Los Angeles zip codes, but 24% (40%) of them live in the 10 (20) most represented zip codes.[25]

Panels A - D of Figure 6 plot the distribution of responses to each survey question. Most respondents believe that buying property is at least a somewhat good investment, but we observe significant heterogeneity in respondents' beliefs about the attractiveness of real estate investments. About 77% of individuals claim to be at least "somewhat well informed" about house prices where their friends live, while 27% are "well informed" or "very well informed." Over half of the respondents report talking at least "sometimes" to their friends about whether buying property is a good investment, while 15% talk "often." Consistent with us finding similar effects of friends' house price experiences during boom and bust periods (see Section 3.4), there is no relationship between an individual's friends' house price experiences and her propensity to talk to her friends about investing in the housing market. Indeed, the average social network house price experiences of the respondents, split up by their responses to Question 3, are 18.4%, 18.3%, 18.3%, and 18.5% respectively.[26] Overall, we find that many individuals regularly interact with their social network to discuss the attractiveness of property investments, suggesting a potentially important role for social interactions in influencing housing market expectations and investments.

We next analyze how the average house price movements in individual i's social network in the 24 months before answering the survey, $FriendHPExp^{All}_{i,2013,2015}$, affect her optimism about property investments in her own zip code. There is significant across-respondent variation in this experience measure, which has a mean of 18.3%, a standard deviation of 2%, and a 10-90 percentile range of 4.5%. Panel E of Figure 6 plots the full distribution of $FriendHPExp^{All}_{i,2013,2015}$ across the survey respondents, while Panel F plots the distribution of the house price experiences of only the friends living outside of the Los Angeles commuting zone.

[24] The wording to this question, which will be our main outcome variable of interest, corresponds to the wording of a question on the New York Fed Survey of Consumer Expectations.

[25] As is generally the case with analyzing survey data, there is some concern that individuals who respond to a survey might be different on important characteristics. While we found the respondents to look similar to the targeted population on observable characteristics, it could be, for example, that those individuals who respond to a housing expectation survey are disproportionately likely to talk to their friends about housing investments.

[26] During the 2013-2015 period, nearly all housing markets in the U.S. saw house price increases. Therefore, our finding suggests that conditional on living in an area with increasing house prices, how much prices increase does not influence how much people talk to their friends about housing market investments. We cannot rule out that such communication becomes more or less common during periods of falling house prices. However, the fact that we found similar-sized effects on investment behavior during both housing booms and housing busts suggests that people talk about their housing market experiences independent of their direction (see Heimer and Simon, 2012; Han and Hirshleifer, 2015, for related discussions).

4.1.2 Analysis of Expectations Survey

Regression 8 analyzes the relationship between the house price experiences of an individual's friends and her belief about whether buying property is a good investment. The dependent variable is an individual's response to Question 4.[27] $\mathbf{X}_i$ controls for the age and gender of the respondent. Since respondents are asked to evaluate the attractiveness of buying property in their own zip code, and the true attractiveness of such investments can vary across zip codes, we also include zip code fixed effects, ψ_{zip}.

$$ResponseQ4_i = \alpha + \beta FriendHPExp^{All}_{i,2013,2015} + \gamma \mathbf{X}_i + \psi_{zip} + \epsilon_i \tag{8}$$

We take two approaches to deal with the ordinal nature of the responses to Question 4. In Table 9 we code the answers to Question 4 with the numbers 1 to 5, with 5 corresponding to the most optimistic view on property investments. This approach assumes that the "distance" between each of the 5 possible answers to Question 4 is the same. Using this coding, the measure of optimism about property investments has a standard deviation of 1.06. Importantly, most of this heterogeneity is across individuals responding about investing in property in the same zip code: when conditioning on ψ_{zip}, the standard deviation of $ResponseQ4_i$ remains at 0.98. As before, we estimate regression 8 using an instrumental variables strategy, where we instrument for the house price experiences of all friends with the house price experiences of only the out-of-commuting zone friends.

Column 1 of Table 9 presents instrumental variables estimates of equation 8. Holding zip code, age, and gender fixed, an increase in friends' house price experiences makes respondents more optimistic about the attractiveness of investing in property. Quantiatively, a one-standard-deviation increase in $FriendHPExp^{All}_{i,2013,2015}$ is associated with a statistically significant 0.08 standard deviation increase in our measure of optimism, $ResponseQ4_i$. It is difficult to assess the magnitude of this effect size. However, in recent work, Armona, Fuster, and Zafar (2016) have analyzed whether differences in an individual's perceived house price experience in her own zip code affect her beliefs about the attractiveness of housing investments (evidence for such extrapolative expectations has also been documented by Kuchler and Zafar, 2015). In particular, they analyze responses to a survey question identical to Question 4 above. They find that a one-standard-deviation increase in individuals' perceptions of their own local house price gains over the past year is associated with an increase in $ResponseQ4_i$ of about 0.1. They compare these estimates to our findings, and conclude that the effect of expectations of the social dynamics channel that we highlight in this paper is of similar magnitude as the effect of the own-extrapolation channel that is the focus of their research.

For survey respondents that only recently moved to Los Angeles, possibly from areas in which they also have many friends, $FriendHPExp^{OutCZ}_{i,2013,2015}$ might be correlated with their own house price experience, in which case even the instrumental variables strategy could not separate the effect of

[27] Our favorite interpretation of the responses to this question is that they reflect differences in the physical probabilities that respondents assign to different states of the world. However, it is possible that respondents risk-adjust their answers to whether they think that housing is an attractive investment. In that case, different responses to Q4 could also reflect differences in risk-adjustments of respondents whose friends experience different house price movements.

social interactions from that of extrapolative expectations. In column 2, we thus restrict the sample to survey respondents that already lived in Los Angeles in 2012. The results in this subsample are very similar.

A common concern with analyzing survey data is the possibility that the framing and ordering of questions affects the responses. In particular, given the order of questions described above, one might worry that by first asking the respondents whether they knew about house prices where their friends live, one might prime them to place more weight on those friends' experiences when subsequently reporting their own perceptions of the attractiveness of housing market investments. To rule out such effects, for about 35% of respondents the order of questions was reversed, asking them first about their housing market expectations ("Question 4"), before eliciting responses to the other questions. Column 3 shows that the correlation between a respondent's friends' house price experiences and her own expectations is, if anything, slightly stronger in the sample of respondents who first reported their own housing market perceptions. This suggests that framing effects do not significantly affect our results.

We next provide additional evidence that the correlation between an individual's housing market beliefs and her friends' house price experiences is driven by social interactions, and not by other confounding shocks. In column 4, we interact $FriendHPExp^{All}_{i,2013,2015}$ with each possible response to Question 2. We also include non-interacted indicator variables for each possible response to Question 2, but, in the interest of space, do not report the corresponding coefficients. The relationship between an individual's assessment of whether buying property is a good investment and the house price experiences of her friends is stronger for individuals who report being aware of house prices where their friends live. Similarly, in column 5 we interact $FriendHPExp^{All}_{i,2013,2015}$ with each possible response to Question 3. For respondents who report that they regularly talk to their friends about whether buying property is a good investment, we find a strong relationship between their friends' house price experiences and their own assessment of whether property in their own zip code is a good investment. Indeed, for respondents that sometimes or often talk to their friends about property investments, the effect size is twice as large as the effect size for the average individual. For respondents that rarely or never talk to their friends about investing in the housing market, no statistically significant relationship is found. This finding suggests that the observed correlation is truly driven by social interactions, and not, for example, by people reading local newspapers from areas where they have friends.[28]

We also take a second approach to dealing with the ordinal nature of the responses to Question 4. Appendix Table A9 presents cumulative odds ratios from an ordered logit model, giving us the effect of a one percentage point increase in $FriendHPExp^{All}_{i,2013,2015}$ on the odds of belonging to a certain cate-

[28]Such a "newspaper channel" would be particularly prominent if individuals have actually lived in the geographically distant regions where they have friends, potentially because they grew up there. The fact that we show below that the effects are similar for individuals who grew up in Los Angeles is thus further evidence against a story where people learn about what is going on where their friends live through channels other than social interactions.

gory or higher versus belonging to one of the lower categories.[29] In this specification, we cannot use an instrumental variables approach, but instead directly include the house price experience of all friends. The statistically significant estimate in column 1 suggests that the odds that an individual perceives buying property in her zip code as at least a somewhat good investment increase by a factor of 1.08 for every percentage point increase in the house price appreciation in her social network. The results in the other columns are also consistent with the findings from Table 9. For example, for individuals who report to often talk to their friends about investing in the housing market, a one percentage point increase in the house price experience within their social network increases the probability of perceiving buying local property as an at least somewhat good investment by 25%.

Overall, these results suggest an important role for social interactions in affecting individuals' assessments of the attractiveness of housing market investments. All else equal, an individual perceives property to be a more attractive investment when there are larger house price gains within her social network. These effects are statistically significant, economically large, and more pronounced for those respondents who report to talk with their friends about whether housing is a good investment.

4.2 Reasons for Updating Expectations

Why would an individual's perceptions of the attractiveness of local housing market investments be influenced by the house price movements in those geographically distant areas where she has friends? We next present evidence that can help differentiate between various possible explanations. In particular, we analyze whether we can find evidence in favor of a rational learning story.

A first such story would involve individuals learning through their friends about house price changes elsewhere that are predictive of future Los Angeles house price changes. To test whether such an effect contributes to our findings, Panel A of Table 10 splits individuals into groups based on how predictive the house price experiences of their out-of-commuting zone social networks are for subsequent Los Angeles house price movements.[30] We then obtain separate estimates of the effect of the social network house price experience on the housing investment behavior of each group. There is no evidence that people with more predictive social networks respond systematically differently.

Second, many plausible rational explanations of the behavior we document involve individuals

[29] An ordered logit model presumes the existence of a latent continuous dependent variable, in our case a measure of how good an investment in a house is, that can only be observed as a set of categories, in our case the five possible responses to Question 4. The model imposes that the slope of the response of the latent dependent variable to a one-unit increase in friends' house price experiences is the same for the entire span of the latent variable. Since no consistent estimator for an ordered logit model explicitly incorporates fixed effects, the literature proposes different estimation strategies. We estimate the ordered logit model using the "Blow Up and Cluster (BUC)" approach of Baetschmann, Staub, and Winkelmann (2015). This approach recodes the original dependent variable with 5 categories into 4 different dichotomizations with 4 different thresholds. Each observation of the original data is then duplicated 4 times, once for each dichotomization. After "blowing up" the data, a conditional logit estimation with clustered standard errors is applied to the whole sample. Riedl and Geishecker (2014) show that this BUC approach delivers the most unbiased and efficient parameter estimates.

[30] Specifically, for every individual, we find the correlation between the house price movements in their out-of-commuting zone social network over the previous 24 months, and Los Angeles house price movements over the next 12 months. We estimate this correlation using yearly observations between 1993 and 2012. Varying the time horizons and the sample period does not significantly affect the ordering of individuals by the predictiveness of their social networks' house price experiences.

learning about some fundamental national housing demand shock from observing house price growth across multiple geographies. If this were an important channel, we would expect individuals to respond more to their friends' experiences if these friends were more geographically dispersed, since the average experience of these friends would then be more informative about the national shock. Yet, Panel B of Table 10 shows that the response of individuals to the experiences of their friends does not generally vary with the number of counties these individuals have friends in.

These pieces of evidence point away from a purely rational learning explanation for our findings, though the precise predictions from any such model would be sensitive to the specifics of the underlying framework.[31] This is perhaps unsurprising. Indeed, if the house price movements in a different part of the country were sufficiently informative to affect a rational agent's valuation of a given house by thousands of dollars, then, in a world of rational learning, everybody should update their expectation equally based on these house prices, which are available for free and in real time. Overall, we find the data to be most consistent with a social belief contagion driven by a more mechanical belief-updating along the lines of Shiller (2007, 2008)

4.3 Evidence Against Alternative Causal Channels

We next present evidence against three causal mechanisms other than social interactions through which friends' house price experiences could affect an individual's housing market behavior.

Bequests: A first alternative explanation is that the house price experiences in a person's social network may have a direct wealth or liquidity effect. In particular, if a person has many friends in her hometown where her parents live, increases in house prices in that hometown might affect the value of any property owned by her parents. In that case, if this individual is expecting to inherit a more expensive house, or if her parents have more resources to help her with purchasing a property in Los Angeles, this could influence her purchasing behavior through a channel that is unrelated to social dynamics.

We present three pieces of evidence that suggest this mechanism cannot explain our findings. First, we separately exploit variation in the overall social network house price experience coming from three sub-sets of out-of-commuting zone friends: family members, work colleagues, and college friends. Appendix Figure A12 shows that house price experiences across these three sub-networks are relatively uncorrelated, i.e., it is not necessarily the case that out-of-commuting zone work and college friends live in similar areas as out-of-commuting zone family friends.[32] While an individual

[31] Appendix Table A7 shows that the effect of friends' average house price experience on an individual's investment behavior declines weakly in the educational attainment of that individual, though we cannot reject equality of the coefficients at the 10% level for any of the specifications. While the ability to engage in rational learning is not necessarily related to education levels, there is growing evidence that lower-income and lower-educated individuals are less likely to engage in optimal behavior along a large number of dimensions (e.g., Beshears et al., 2015). The fact that these individuals are, if anything, less likely to respond to their friends' house price experiences provides additional evidence against a rational learning story.

[32] Facebook allows users to self-identify friends that are family members. College friends or work colleagues are identified as Facebook friends who went to the same college or report the same employer. Since not all individuals identify family members, or report where they work and went to college, sample sizes are somewhat smaller in these specifications.

might expect higher future bequests when her family members experience higher house price growth, this is less likely to be the case for her college or work friends. Yet, Appendix Table A10 shows that the influence of the house price experiences in all three sub-networks on investment behavior is very similar, suggesting the bequest channel is relatively unimportant.

As a second piece of evidence against a bequest story, we show that our estimates are similar among individuals whose bequests are less likely to be affected by the house price movements of their U.S.-based out-of-commuting-zone friends. In particular, Appendix Table A11, Panel A, shows the effects of friends' house price experiences on housing investments when restricting the sample to individuals whose hometown is Los Angeles, and Panel B shows these effects when restricting the sample to individuals whose hometown is outside of the United States. We find similarly-sized effects in both subgroups of the population, even though these individuals are less likely to experience increases in expected bequests when the house prices in their social networks increase.

Third, since most individuals can only expect bequests from a few close relatives within their social network, a bequest channel should be stronger when individuals' social networks are more geographically concentrated, and friends' overall house price experience more closely corresponds to that of those close relatives. Yet, Panel B of Table 10 shows that the effects are unrelated to how many counties an individual has friends in, providing further evidence against a bequest story.

Consumption Externalities: A second alternative explanation for our findings is the possible presence of consumption externalities across individuals and their friends. For example, an individual might buy a house to "keep up with the Joneses" after her friends purchased a home. However, notice that in the construction of our key explanatory variable in equation 1, we never actually use whether an individual's friends have purchased a house. Indeed, the house price experiences of renters and owners count equally. However, this does not completely alleviate the potential of consumption externalities to explain at least some of our findings. Since house prices and transaction volumes co-move, people are more likely to buy a house on average in regions where house prices go up. $FriendHPExp$ could therefore be picking up the effect of friends' buying behavior on individuals' own investments, even though the actual behavior of an individual's friends is not used to construct this measure.

To see whether this is a likely explanation for our findings, Appendix Table A12 introduces controls for the change and level of trading volume in the counties where an individual has friends. The estimated effects of friends' house price experiences are nearly identical, suggesting that they are not just picking up a desire to keep up with friends.[33]

Robustness checks confirm that our baseline effect in these sub-samples is similar to the baseline effect in the full sample.

[33] Trading volume is measured as the annualized share of housing stock that transacts, and is obtained from Zillow. These data are only available since 1998; which reduces the sample sizes for the price paid and size bought regressions. The fact that controling for changes in trading volume does not significantly affect the effect of price changes on investment behavior is consistent with the observation that, in the cross-section, county-level house price changes and price changes over the previous 24 months are nearly uncorrelated (the conditional correlation of the two measures in the Zillow data is 0.02). This, in turn, is largely driven by the well-known fact that trading volume leads house price changes in the time-series by about 18 months.

Hedging: A further alternative story that could explain our results is if individuals are eventually planning to move to those parts of the country where they have friends. In that case, when they see house prices there go up, they might want to purchase a house themselves in order to hedge against further price increases that might price them out of the market (see Sinai and Souleles, 2013). If this were an important force explaining our results, one would expect the effect to be larger for people whose friends live in housing markets that are more correlated with Los Angeles, and for which Los Angeles housing would thus provide a better hedge. Yet, Panel A of Table 10 shows that this is not the case.

5 Conclusion

In this paper, we document that the house price experiences within an individual's social network affect her perceptions of the attractiveness of property investments, and through this channel have large effects on her housing market activity. We overcome the pertinent measurement challenge in the social network literature by exploiting anonymized individual-level data from Facebook, highlighting the power of such data to help researchers to better understand the role of social networks in economic and financial decision making.

Our results show that social interactions play an important role in determining how people form expectations as well as in explaining their actual investment behavior. The effects are quantitatively large, and have the potential to affect aggregate outcomes. Indeed, in follow-on work, Bailey, Cao, Kuchler, Stroebel, and Vavra (2016a) show that the individual-level effects documented in this paper aggregate up to affect county-level prices and trading volumes. This suggests that, at the county level, friendship networks provide a mechanism that can propagate house price shocks through the economy.

While we document the effect of social interactions on expectations and investment behavior in the housing market, it is likely that similar social dynamics are also at work in other settings. For example, it is possible that optimism and pessimism about stock market investments, or sentiments about the economy more generally, also spread social interactions in a similar way. We hope that the increasing availability of online social network data will facilitate research along a number of these dimensions. One interesting question left unexplored in this paper is whether the increasing connectedness of individuals through social media will itself have an effect on how the experiences of individuals influence the behavior of their geographically distant friends across a number of settings.

References

Acemoglu, Daron, Munther A Dahleh, Ilan Lobel, and Asuman Ozdaglar. 2011. "Bayesian learning in social networks." *The Review of Economic Studies* 78 (4):1201–1236.

Akerlof, George A and Robert J Shiller. 2010. *Animal spirits: How human psychology drives the economy, and why it matters for global capitalism*. Princeton University Press.

Angeletos, George-Marios and Jennifer La'O. 2013. "Sentiments." *Econometrica* 81 (2):739–779.

Armona, Luis, Andreas Fuster, and Basit Zafar. 2016. "Home Price Expectations and Behavior: Evidence from a Randomized Information Experiment." .

Baetschmann, Gregori, Kevin E. Staub, and Rainer Winkelmann. 2015. "Consistent estimation of the fixed effects ordered logit model." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 178 (3):685–703. URL http://dx.doi.org/10.1111/rssa.12090.

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, Johannes Stroebel, and Joseph Vavra. 2016a. "Prices and Trading Volumes in the Housing Markets: The Role of Disagreements and Social Networks." .

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong. 2016b. "Measuring Social Connectedness." .

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer. 2015. "Extrapolation and bubbles." *Working Paper* .

Barberis, Nicholas and Richard Thaler. 2003. "A survey of behavioral finance." *Handbook of the Economics of Finance* 1:1053–1128.

Bayer, Patrick, Christopher Geissler, Kyle Mangum, and James W Roberts. 2016. "Speculative fever: Investor contagion in the housing bubble." .

Berger, David, Veronica Guerrieri, Guido Lorenzoni, and Joseph Vavra. 2015. "House prices and consumer spending." Tech. rep., National Bureau of Economic Research.

Beshears, John, James J Choi, David Laibson, Brigitte C Madrian, and Sean Yixiang Wang. 2015. "Who Is Easier to Nudge?" Tech. rep., Working Paper.

Bracha, Anat and Julian C Jamison. 2012. "Shifting confidence in homeownership: The great recession." *BE Journal of Macroeconomics* .

Brunnermeier, Markus K, Alp Simsek, and Wei Xiong. 2014. "A Welfare criterion for models with distorted beliefs." *Quarterly Journal of Economics* 129 (4):1753–1797.

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo. 2016. "Understanding booms and busts in housing markets." *Journal of Political Economy, forthcoming* .

Choi, James J, David Laibson, Brigitte C Madrian, and Andrew Metrick. 2009. "Reinforcement learning and savings behavior." *Journal of Finance* 64 (6):2515–2534.

Conley, Timothy G and Christopher R Udry. 2010. "Learning about a new technology: Pineapple in Ghana." *American Economic Review* 100 (1):35–69.

Cookson, Anthony and Marina Niessner. 2016. "Why don't we agree? Evidence from a social network of investors." .

Dávila, Eduardo. 2014. "Optimal financial transaction taxes." *Working Paper* .

Facebook. 2016. "Facebook Form 10-Q, Quarterly Report, Q3." .

Favara, Giovanni and Zheng Song. 2014. "House price dynamics with dispersed information." *Journal of Economic Theory* 149:350–382.

Geanakoplos, John. 2009. "The leverage cycle." In *NBER Macroeconomics Annual 2009, Volume 24*, edited by D. Acemoglu, K. Rogoff, and M. Woodford. University of Chicago Press, 1–65.

Gilbert, Eric and Karrie Karahalios. 2009. "Predicting tie strength with social media." In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 211–220.

Glaeser, Edward L and Charles G Nathanson. 2015. "An extrapolative model of house price dynamics." *Working Paper* .

Glaeser, Edward L, Bruce Sacerdote, and José A Scheinkman. 1996. "Crime and Social Interactions." *The Quarterly Journal of Economics* 111 (2):507–548.

Golub, Benjamin and Evan Sadler. 2015. "Learning in social networks."

Granovetter, Mark. 2005. "The impact of social structure on economic outcomes." *The Journal of economic perspectives* 19 (1):33–50.

Greenwood, Robin and Andrei Shleifer. 2014. "Expectations of returns and expected returns." *Review of Financial Studies* 27:714–746.

Guren, Adam. 2015. "The causes and consequences of house price momentum." Tech. rep.

Hampton, Keith, Lauren Sessions Goulet, Lee Rainie, and Kristen Purcell. 2011. "Social networking sites and our lives. Pew internet and american life project."

Han, Bing and David Hirshleifer. 2015. "Self-enhancing transmission bias and active investing." *Working Paper* .

Harrison, J Michael and David M Kreps. 1978. "Speculative investor behavior in a stock market with heterogeneous expectations." *Quarterly Journal of Economics* 92 (2):323–336.

Heimer, Rawley Z and David Simon. 2012. "Facebook finance: How social interaction propagates active investing."

Hong, Harrison and Jeremy C Stein. 1999. "A unified theory of underreaction, momentum trading, and overreaction in asset markets." *Journal of Finance* 54 (6):2143–2184.

———. 2007. "Disagreement and the stock market." *Journal of Economic Perspectives* 21 (2):109–128.

Ioannides, Yannis M and Linda Datcher Loury. 2004. "Job information networks, neighborhood effects, and inequality." *Journal of economic literature* 42 (4):1056–1093.

Jackson, Matthew O. 2014. "Networks in the understanding of economic behaviors." *The Journal of Economic Perspectives* 28 (4):3–22.

Jones, Jason J, Jaime E Settle, Robert M Bond, Christopher J Fariss, Cameron Marlow, and James H Fowler. 2013. "Inferring tie strength from online directed behavior." *PloS ONE* 8 (1):e52168.

Kaplan, Greg, Kurt Mitman, and Giovanni L Violante. 2015. "Consumption and house prices in the Great Recession: Model meets evidence." Tech. rep., NYU Working Paper.

Kuchler, Theresa and Basit Zafar. 2015. "Personal experiences and expectations about aggregate outcomes." *Federal Reserve Bank of New York Staff Reports* 748.

Landvoigt, Tim. 2014. "Housing demand during the boom: The role of expectations and credit constraints." *Working Paper* .

Malmendier, Ulrike and Stefan Nagel. 2011. "Depression babies: Do macroeconomic experiences affect risk taking?" *The Quarterly Journal of Economics* 126 (1):373–416.

———. 2015. “Learning from inflation experiences.” *Quarterly Journal of Economics* Forthcoming.

Manski, Charles F. 1993. “Identification of endogenous social effects: The reflection problem.” *The Review of Economic Studies* 60 (3):531–542.

Miller, Edward M. 1977. “Risk, uncertainty, and divergence of opinion.” *Journal of Finance* 32 (4):1151–1168.

Montgomery, James D. 1991. “Social networks and labor-market outcomes: Toward an economic analysis.” *The American economic review* 81 (5):1408–1418.

Moretti, Enrico. 2011. “Social learning and peer effects in consumption: Evidence from movie sales.” *The Review of Economic Studies* 78 (1):356–393.

Nathanson, Charles G and Eric Zwick. 2014. “Arrested development: Theory and evidence of supply-side speculation in the housing market.” Tech. rep.

Piazzesi, Monika and Martin Schneider. 2009. “Momentum traders in the housing market: Survey evidence and a search model.” *American Economic Review* 99 (2):406–11. URL http://www.aeaweb.org/articles.php?doi=10.1257/aer.99.2.406.

Piazzesi, Monika, Martin Schneider, and Johannes Stroebel. 2015. “Segmented housing search.” *Working Paper* .

Riedl, Maximilian and Ingo Geishecker. 2014. “Keep it simple: Estimation strategies for ordered response models with fixed effects.” *Journal of Applied Statistics* 41 (11):2358–2374.

Scheinkman, Jose A and Wei Xiong. 2003. “Overconfidence and speculative bubbles.” *Journal of Political Economy* 111 (6):1183–1220.

Shiller, Robert J. 2007. “Understanding recent trends in house prices and home ownership.” Tech. rep., National Bureau of Economic Research.

———. 2008. “Infectious Exuberance.” Tech. rep., The Atlantic.

———. 2015. *Irrational exuberance*. Princeton University Press.

Simsek, Alp. 2013a. “Belief disagreements and collateral constraints.” *Econometrica* 81 (1):1–53.

———. 2013b. “Speculation and risk sharing with new financial assets.” *Quarterly Journal of Economics* 128 (3):1365–1396.

Sinai, Todd and Nicholas Souleles. 2013. “Can owning a home hedge the risk of moving?” *American Economic Journal: Economic Policy* 5 (2):282–312.

Vissing-Jorgensen, Annette. 2003. “Perspectives on behavioral finance: Does "irrationality" disappear with wealth? Evidence from expectations and actions.” In *NBER Macroeconomics Annual 2003, Volume 18*. The MIT Press, 139–208.

Wheaton, William C. 1990. “Vacancy, search, and prices in a housing market matching model.” *Journal of Political Economy* 98 (6):1270–1292.

Table 1: Summary Statistics - Change-of-Tenure Sample

	Mean	SD	P5	P10	P25	P50	P75	P90	P95
Number of Friends									
All Friends	304	406	35	49	90	184	358	655	943
Out-of-Commuting Zone Friends	125	236	13	16	27	56	126	278	447
Average Friend Appreciation 2008-10									
All Friends	-7.08%	1.78%	-10.08%	-8.96%	-7.73%	-6.79%	-6.08%	-5.54%	-5.15%
Out-of-Commuting Zone Friends	-10.34%	3.39%	-16.25%	-14.69%	-12.34%	-10.07%	-8.14%	-6.42%	-5.23%
Average Friend Appreciation 2010-12									
All Friends	4.32%	1.41%	2.13%	2.98%	3.91%	4.43%	4.86%	5.47%	6.05%
Out-of-Commuting Zone Friends	4.56%	2.35%	0.75%	1.85%	3.32%	4.65%	5.85%	7.09%	8.06%
Income 2010 (K$)	69.90	41.47	10	18	35	63	88	150	150
Income Change 2010-12 (K$)	0.71	23.12	-35	-18	0	0	0	18	38
Household Size 2010	3.02	1.74	1	1	2	3	4	6	6
Household Size Change 2010-12	-0.10	1.26	-2	-1	0	0	0	1	2
Age 2010	41.03	15.09	20	24	31	41	51	61	66
Home Ownership Development 2010-12									
Stayed Renter	0.24	0.43	0	0	0	0	0	1	1
Became Homeowner	0.05	0.22	0	0	0	0	0	0	1
Stayed Homeowner	0.66	0.47	0	0	0	1	1	1	1
Become Renter	0.05	0.21	0	0	0	0	0	0	0
Family Structure Development 2010-12									
Stayed Single	0.42	0.49	0	0	0	0	1	1	1
Got Married	0.06	0.24	0	0	0	0	0	0	1
Stayed Married	0.47	0.50	0	0	0	0	1	1	1
Got Divorced	0.06	0.23	0	0	0	0	0	0	1
Education 2010									
Has High School	0.47	0.50	0	0	0	0	1	1	1
Has College Degree	0.37	0.48	0	0	0	0	1	1	1
Has Graduate Degree	0.15	0.36	0	0	0	0	0	1	1

Note: Table shows summary statistics for the change-of-tenure regression sample analyzed in Section 3.1. See Section 1.2 for details on the sample construction. For each characteristic, we show the mean, standard deviation, and the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the distribution.

Table 2: Summary Statistics - Transaction Sample

	Mean	SD	SD | Q	SD | Q & Zip Code	P10	P25	P50	P75	P90
Transaction Characteristics									
Transaction Price (USD)	403,344	293,533	263,173	180,244	125,000	175,000	325,000	550,000	750,000
Origination LTV (%)	85.44	17.26	17.07	15.31	68.18	73.33	84.62	100.00	100.00
Property Characteristics									
Is SFR	0.77	0.42	0.42	0.36	0	1	1	1	1
Property Size (Sqft)	1,775	870	868	742	988	1,217	1,566	2,107	2,829
Lot Size (Sqft)	9,452	9,374	9,302	8,200	2,500	7,500	7,500	7,500	15,500
Age of Property (Years)	40.46	24.66	24.45	17.55	5	21	43	56	74
Has Pool	0.23	0.42	0.42	0.38	0	0	0	0	1
Buyer Characteristics									
Number of Friends									
All Friends	408	503	502	482	60	117	245	502	917
Out-of-Commuting Zone Friends	156	262	262	249	18	34	74	170	360
Average 24-M Friend Appreciation									
All Friends	7.7%	20.1%	3.5%	3.3%	-21.0%	-5.7%	10.6%	21.3%	34.0%
Out-of-Commuting Zone Friends	6.6%	15.5%	4.0%	3.7%	-16.9%	-2.2%	9.4%	17.0%	23.8%
Age at Purchase	35.45	14.33	14.11	13.31	18	28	35	43	52
Has High School Degree in 2010	0.43	0.50	0.49	0.47	0	0	0	1	1
Has College Degree in 2010	0.38	0.49	0.49	0.47	0	0	0	1	1
Has Graduate Degree in 2010	0.2	0.4	0.4	0.4	0	0	0	0	1
Income in 2010 (K$)	79.5	41.2	40.8	32.0	25.0	45.0	62.5	112.5	150.0
Household Size in 2010	3.1	1.7	1.6	1.5	1	2	3	4	5
Married in 2010	0.6	0.5	0.5	0.4	0	0	1	1	1

Note: Table shows summary statistics for the transaction regression sample analyzed in Sections 3.2 and 3.3. See Section 1.2 for details on the sample construction. For each characteristic, we show the mean, standard deviation, within-quarter standard deviation, within-quarter-zip-code standard deviation, and the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution.

Table 3: Summary Statistics - Characteristics of Social Networks

	Mean	SD	P5	P10	P25	P50	P75	P90	P95
Number of Counties with Friends	55.5	59.9	13	15	22	37	67	112	151
Share of Friends Living Within									
LA Commuting Zone	62.9%	19.8%	22.4%	32.8%	51.4%	67.9%	78.2%	84.4%	87.1%
California	70.4%	19.2%	28.7%	41.2%	61.8%	76.4%	84.3%	89.0%	91.0%
200 Miles	65.5%	19.9%	23.9%	35.1%	54.6%	70.9%	80.5%	86.2%	88.6%
500 Miles	74.7%	19.3%	32.2%	45.2%	66.7%	81.1%	88.6%	92.8%	94.5%
1,000 Miles	79.1%	18.2%	38.0%	51.7%	73.1%	85.7%	91.6%	94.8%	96.2%
Share of Out-of-CZ Friends by Census Division									
Pacific	32.4%	18.6%	5.7%	9.1%	17.8%	30.9%	44.7%	57.8%	66.7%
Mountain	20.1%	14.8%	2.5%	4.3%	8.5%	17.0%	28.6%	40.5%	48.5%
West North Central	3.4%	6.6%	0.0%	0.0%	0.0%	1.8%	4.1%	7.7%	11.8%
East North Central	7.3%	10.3%	0.0%	0.0%	1.9%	4.6%	8.3%	15.5%	25.0%
Mid Atlantic	9.2%	12.1%	0.0%	0.0%	1.5%	5.5%	11.8%	22.7%	34.3%
New England	2.8%	6.0%	0.0%	0.0%	0.0%	1.1%	3.4%	6.7%	10.0%
West South Central	10.3%	10.6%	0.0%	1.3%	4.0%	7.6%	13.2%	21.3%	29.2%
East South Central	2.3%	4.7%	0.0%	0.0%	0.0%	1.0%	3.0%	5.9%	8.3%
South Atlantic	12.0%	11.2%	0.0%	1.6%	5.3%	9.3%	15.4%	23.8%	32.3%
Share of Friends in Age Group									
18-24	12.8%	20.1%	0.2%	1.0%	2.3%	5.4%	12.3%	33.3%	70.8%
25-34	29.2%	22.5%	4.6%	6.7%	11.7%	21.5%	42.2%	66.7%	75.5%
35-44	23.8%	16.9%	2.5%	4.6%	10.8%	20.4%	33.3%	48.9%	57.5%
45-54	17.5%	15.0%	1.0%	1.9%	5.4%	13.9%	25.6%	38.5%	48.0%
55-64	9.9%	11.5%	0.0%	0.6%	2.0%	5.4%	14.0%	26.4%	33.9%
65+	6.7%	8.5%	0.3%	0.8%	1.9%	4.0%	7.9%	15.4%	23.7%
Share of Friends by Education									
Unknown	16.1%	16.3%	3.4%	6.6%	10.5%	15.1%	20.9%	28.6%	34.7%
Highschool	18.9%	11.0%	4.0%	5.9%	10.5%	18.1%	26.3%	32.7%	36.5%
College	53.6%	13.6%	34.5%	39.3%	46.7%	54.0%	60.5%	66.6%	70.5%
Graduate School	11.4%	10.2%	1.2%	2.1%	4.2%	8.5%	15.5%	24.4%	31.6%

Note: Table shows summary statistics on the U.S. social networks of the individuals in the change-of-tenure sample. For each characteristic, we show the mean, standard deviation, and the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the distribution.

Table 4: Network Characteristics

	Number Counties	Share Friends Living Within					Share Friends in Age Group (Years)						Share Friends by Highest Education Level			
		LA CZ	CA	200 mi	500 mi	1000 mi	18-24	25-34	35-44	45-54	55-64	65+	Unknown	HS	College	Grad
	PANEL A: Average of Network Characteristic by Individual Characteristics															
Full Sample	55.5	62.9%	70.4%	65.5%	74.7%	79.1%	12.8%	29.2%	23.8%	17.5%	9.9%	6.7%	16.1%	18.9%	53.6%	11.4%
Age																
18-24	57.1	75.3%	81.3%	77.1%	84.8%	87.7%	68.6%	20.9%	5.0%	2.9%	1.3%	1.3%	14.5%	22.9%	58.0%	4.7%
25-34	60.8	65.9%	73.5%	68.4%	77.6%	81.4%	12.5%	60.0%	16.1%	6.1%	2.9%	2.4%	15.1%	18.1%	54.6%	12.2%
35-44	57.0	62.8%	70.2%	65.3%	74.5%	78.8%	6.3%	24.1%	44.8%	15.0%	5.4%	4.4%	17.0%	18.6%	51.7%	12.7%
45-54	55.1	61.1%	68.4%	63.6%	72.9%	77.5%	6.1%	15.2%	22.8%	37.5%	11.7%	6.6%	16.6%	19.6%	52.8%	10.9%
55-64	48.6	57.7%	65.8%	60.6%	70.3%	75.7%	5.2%	14.7%	16.8%	22.5%	29.2%	11.6%	16.2%	18.5%	53.6%	11.6%
65+	45.0	54.5%	63.2%	57.6%	67.7%	73.7%	5.1%	13.8%	18.0%	20.1%	19.3%	23.6%	16.3%	17.4%	53.5%	12.7%
Education																
Unknown	41.0	61.8%	69.2%	64.3%	73.8%	78.3%	10.9%	25.8%	25.3%	19.2%	11.1%	7.7%	20.2%	19.8%	50.4%	9.5%
Highschool	44.6	67.3%	73.7%	69.9%	78.9%	83.1%	15.4%	27.7%	23.2%	18.0%	9.6%	6.1%	17.5%	25.6%	50.5%	6.4%
College	60.8	63.0%	70.6%	65.5%	74.6%	79.0%	13.8%	30.3%	22.9%	16.9%	9.6%	6.5%	14.9%	17.7%	56.2%	11.2%
Graduate School	73.6	56.3%	65.8%	58.8%	68.7%	73.6%	6.3%	31.7%	27.5%	17.4%	9.9%	7.1%	12.7%	10.7%	51.7%	24.9%
Gender																
Female	52.3	64.0%	71.5%	66.6%	75.8%	80.1%	12.2%	28.8%	24.0%	17.7%	10.3%	6.9%	16.2%	19.3%	53.2%	11.3%
Male	59.9	61.4%	69.0%	63.8%	73.2%	77.7%	13.8%	29.6%	23.6%	17.3%	9.4%	6.4%	15.9%	18.4%	54.2%	11.5%
	PANEL B: Predictive Power (R-Squared) of Individual Characteristics for Network Characteristic															
Age	0.5%	6.0%	5.3%	5.3%	4.6%	3.5%	73.5%	68.6%	59.1%	62.1%	61.9%	53.4%	0.3%	1.5%	1.6%	4.5%
Education	2.5%	2.3%	1.3%	2.3%	2.1%	2.0%	1.6%	0.4%	0.8%	0.2%	0.0%	0.2%	2.1%	15.1%	4.3%	25.8%
Gender	0.4%	0.4%	0.3%	0.4%	0.4%	0.4%	0.2%	0.0%	0.0%	0.0%	0.2%	0.1%	0.0%	0.3%	0.2%	0.0%
Zip	6.1%	8.4%	6.7%	8.4%	8.6%	8.3%	6.0%	3.6%	1.3%	4.2%	4.6%	4.3%	2.5%	23.8%	5.4%	20.9%
Hometown	12.0%	35.4%	37.7%	36.3%	40.5%	42.2%	7.6%	5.8%	4.1%	6.1%	9.7%	11.2%	8.8%	25.2%	12.2%	22.9%
Income	0.7%	1.3%	0.6%	1.1%	1.1%	0.8%	2.0%	3.1%	0.6%	3.6%	4.6%	3.8%	1.4%	7.6%	2.5%	7.6%
Occupation	0.5%	1.6%	1.3%	1.4%	1.5%	1.1%	7.1%	8.7%	1.3%	8.7%	10.2%	10.2%	0.4%	3.4%	0.6%	4.2%
All of the Above	16.0%	38.7%	40.0%	39.1%	42.6%	43.9%	76.2%	70.4%	61.1%	64.3%	64.8%	57.4%	10.6%	41.7%	18.8%	48.3%

Note: Table shows summary statistics on the U.S. social networks of the individuals in the change-of-tenure sample. Panel A shows average values of network characteristics for sub-groups of our sample. Panel B presents adjusted R-squared values from regressions of the network characteristics on dummy variables for each value of the respective individual characteristics.

Table 5: Social Networks: Sample vs. Rest of U.S.

	Share of Friends within 200 Miles			Share of Friends within 500 Miles		
	Median Person	95-5 Range	75-25 Range	Median Person	95-5 Range	75-25 Range
Sample	70.9%	64.7%	25.9%	67.9%	62.3%	22.0%
Statistics Across Counties (weighted by population)						
Mean	72.8%	77.2%	30.1%	83.6%	65.9%	20.9%
P5	54.5%	61.5%	15.0%	70.0%	42.4%	8.5%
P10	59.6%	64.8%	16.5%	73.3%	46.6%	9.9%
P25	67.6%	72.8%	19.8%	81.7%	54.5%	12.4%
P50	74.4%	79.3%	28.3%	85.2%	67.6%	17.9%
P75	80.0%	83.1%	38.7%	88.4%	79.3%	26.6%
P90	83.3%	85.1%	46.8%	90.4%	82.9%	37.6%
P95	84.7%	86.6%	49.9%	91.7%	84.7%	42.5%

Note: Table shows summary statistics on the U.S. social networks of the individuals in the change-of-tenure sample, as well as population-weighted statistics across U.S. counties.

Table 6: Probability of Owning in 2012

	Panel A - 2010 Renters					
	Dependent Variable: P(Owner in 2012) in %					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Friend County House Prices 2008-2010 (%)	0.608***	0.514***	0.511***	0.501***	0.544***	0.672***
	(0.042)	(0.065)	(0.044)	(0.169)	(0.043)	(0.043)
Δ Friend County Income 2008-2010 (%)					0.332***	
					(0.033)	
Δ Friend County House Prices 2010-2012 (%)						0.324***
						(0.044)
Zip 2010 X Zip 2012 FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Sample Restriction		Only Full Set of Controls	Stayed in Same Zip Code	Geographically Non-Clustered Professions		
N	433,836	156,764	302,686	433,836	433,836	433,836
R-Squared	0.434	0.463	0.125	0.434	0.434	0.434
Mean Dependent Variable	0.178	0.195	0.103	0.178	0.178	0.178
	Panel B - 2010 Owners					
	Dependent Variable: P(Owner in 2012) in %					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Friend County House Prices 2008-2010 (%)	0.201***	0.137***	0.092***	0.088***	0.190***	0.221***
	(0.015)	(0.017)	(0.013)	(0.032)	(0.016)	(0.016)
Δ Friend County Income 2008-2010 (%)					0.049***	
					(0.011)	
Δ Friend County House Prices 2010-2012 (%)						0.095***
						(0.016)
Zip 2010 X Zip 2012 FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Sample Restriction		Only Full Set of Controls	Stayed in Same Zip Code	Geographically Non-Clustered Professions		
N	1,035,523	621,143	892,250	1,035,523	1,035,523	1,035,523
R-Squared	0.564	0.552	0.136	0.564	0.564	0.564
Mean Dependent Variable	0.935	0.951	0.981	0.935	0.935	0.935

Note: Table shows results from regression 5. The dependent variable is an indicator capturing whether the individual is a homeowner in 2012. Panel A focuses on individuals that were renting in 2010, Panel B on individuals that were owning in 2010. All specifications control for 2010 and 2012 zip code pair fixed effects, as well as demographic characteristics of the individuals. The house price experiences of all friends are instrumented for by the house price experiences of out-of-commuting zone friends. Column 2 restricts the sample to individuals for whom the entire set of demographic controls is available, whereas all other columns replace missing demographics with a unique fixed effect. Column 3 shows results for individuals who stayed in the same zip code. Column 4 only exploits variation in friends' house price experiences among individuals who are retired or work in non-geographically clustered professions. Column 5 adds the average income changes in the friends' counties between 2008 and 2010 as a separate control. Column 6 adds friends' house price changes between 2010 and 2012 as a separate control. Standard errors are clustered at the 2010 zip code level. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table 7: Size of Property Purchased

	Dependent Variable: 100 x log(Property Size)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Friend County House Prices Past 24 Months (%)	0.310*** (0.053)	0.252*** (0.037)	0.520*** (0.144)	0.530*** (0.164)	0.400*** (0.060)	0.234*** (0.079)	0.285*** (0.056)
Δ Friend County Income Past 24 Months (%)							0.173*** (0.096)
Month FE	Y	Y	Y	Y	Y	Y	Y
Buyer Controls	Y	Y	Y	Y	Y, x Year	Y	Y
Sample Notes and Additional FE		ZIP Code FE	Purchases Since 2010	Purchases Since 2010, Lived in LA in 2010		Geographically Non-Clustered Professions	
N	526,594	526,594	95,561	68,388	526,593	526,594	526,594
R-Squared	0.194	0.325	0.134	0.126	0.204	0.194	0.194

Note: Table shows results from regression 6. The dependent variable is the log of property size, multiplied by 100. Sample is the transaction sample described in Section 1.2. The house price experiences of all friends are instrumented for by the house price experiences of out-of-commuting zone friends. All columns control for purchase month fixed effects and buyer characteristics. Column 2 adds zip code fixed effects to the baseline regression. Column 3 restricts the sample to house purchases since 2010; column 4 further restricts this to purchases since 2010 where the buyers lived in Los Angeles county in 2010. In column 5, we interact buyer characteristics with year-of-transaction fixed effects. Column 6 only exploits variation in friends' house price appreciation among buyers who are retired or work in non-geographically clustered professions. Column 7 adds the average income changes in the friends' counties in the 24 months prior to the transaction as a separate control. Standard errors are clustered at the purchase-month level. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table 8: Transaction Price

	Panel A: Main Results Dependent Variable: 100 x log(Price)				
	(1)	(2)	(3)	(4)	(5)
Δ Friend County House Prices Buyer - Past 24 Months (%)	0.452*** (0.015)	0.486*** (0.050)	0.408*** (0.076)	0.445*** (0.015)	0.335*** (0.068)
Δ Friend County House Prices Seller - Past 24 Months (%)				0.233*** (0.059)	0.289** (0.112)
Year x Zip Code FE	Y	Y	Y	Y	Y
Property Controls	Y	N	Y	Y	N
Buyer Controls	Y	Y	N	Y	Y
Sample or Specification Notes		Property FE	Buyer FE		Property FE
N	523,299	34,732	32,226	523,299	33,230
R-Squared	0.808	0.950	0.948	0.809	0.956

	Panel B: Robustness Checks Dependent Variable: 100 x log(Price)				
	(1)	(2)	(3)	(4)	(5)
Δ Friend County House Prices Buyer - Past 24 Months (%)	0.468*** (0.029)	0.461*** (0.032)	0.489*** (0.016)	0.423*** (0.043)	0.441*** (0.015)
Δ Friend County Income Buyer - Past 24 Months (%)					0.128*** (0.043)
Year x Zip Code FE	Y	Y	Y	Y	Y
Property Controls	Y	Y	Y	Y	Y
Buyer Controls	Y	Y	Y, x Year	Y	Y
Sample or Specification Notes	Purchases Since 2010	Purchases Since 2010, Rented in 2010		Geographically Non-Clustered Professions	
N	95,226	68,202	523,299	523,299	523,299
R-Squared	0.842	0.847	0.809	0.810	0.808

Note: Table shows results from regression 7, where the dependent variable is the log of transaction price of home purchase, multiplied by 100. Sample is the transaction sample described in Section 1.2. The house price experiences of all friends are instrumented for by the house price experiences of out-of-commuting zone friends. All columns control for year-of-purchase by zip code fixed effects, as well as property and buyer characteristics. In Panel A, columns 2 and 5 also include property fixed effects, and column 3 includes buyer fixed effects. Columns 4 and 5 include the house price experiences of the sellers' social networks, instrumented for by their out-of-commuting zone counterparts. Panel B presents robustness checks. Column 1 restricts the sample to house purchases since 2010; column 2 further restricts this to purchases since 2010 where the buyers lived in Los Angeles county in 2010. In column 3, we interact buyer characteristics with year-of-transaction fixed effects. Column 4 only exploits variation in friends' house price appreciation among buyers who are retired or work in non-geographically clustered professions. Column 5 adds the average income changes in the buyers' friends' counties in the 24 months prior to the transaction as a separate control. Standard errors are clustered at the zip code level. Significance Levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

Table 9: Expectation Of Whether Buying Property is a Good Investment

	(1)	(2)	(3)	(4)	(5)
Δ Friend County House Prices 2013-2015 (%)	0.04**	0.036*			
	(0.017)	(0.019)			
Δ Friend County House Prices 2013-2015 (%) x Ordering of Question					
Expectation Question Last			0.039**		
			(0.021)		
Expectation Question First			0.048*		
			(0.029)		
Δ Friend County House Prices 2013-2015 (%) x Knowledge of HP in Friends' Location					
Not at all informed				0.002	
				(0.036)	
Somewhat informed				0.036	
				(0.023)	
Well informed				0.068*	
				(0.039)	
Very well informed				0.119*	
				(0.069)	
Δ Friend County House Prices 2013-2015 (%) x Talk with Friend about Housing Investment					
Never					-0.050
					(0.038)
Rarely					0.001
					(0.028)
Sometimes					0.086***
					(0.027)
Often					0.096**
					(0.049)
Demographic Controls	Y	Y	Y	Y	Y
Zip Code Fixed Effects	Y	Y	Y	Y	Y
Sample		LA in 2012			
N	1,242	1,110	1,242	1,242	1,242

Note: Table shows results from regression 8. The dependent variable is the answer to survey Question 4: "If someone had a large sum of money that they wanted to invest, would you say that relative to other possible financial investments, buying property in your zip code today is: (1) A very bad investment, (2) A somewhat bad investment, (3) Neither good nor bad as an investment, (4) A somewhat good investment, or (5) A very good investment, with the 5 (ordered) answers recoded to 1-5. The house price experiences of all friends are instrumented for by their out-of-commuting zone counterparts. Column 1 shows the baseline estimates. Column 2 restricts the sample to respondents who lived in LA in 2012. The last three columns estimate differential effects by the ordering of the questions (column 3), by how informed respondents claimed to be about house prices in their friends' zip codes (column 4), and by how often they reported talking to their friends about investing in property (column 5). The specifications in columns 4, 5, and 6 also include non-interacted indicator variables for the question ordering, and the possible responses to Questions 2 and 3, respectively; in the interest of space, the corresponding coefficients are not reported. All columns also control for respondent age and gender. Standard errors are in parentheses. Significance Levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

Table 10: Differential Effects by Network Predictiveness and Network Size

Panel A: Effects by Predictiveness of Network

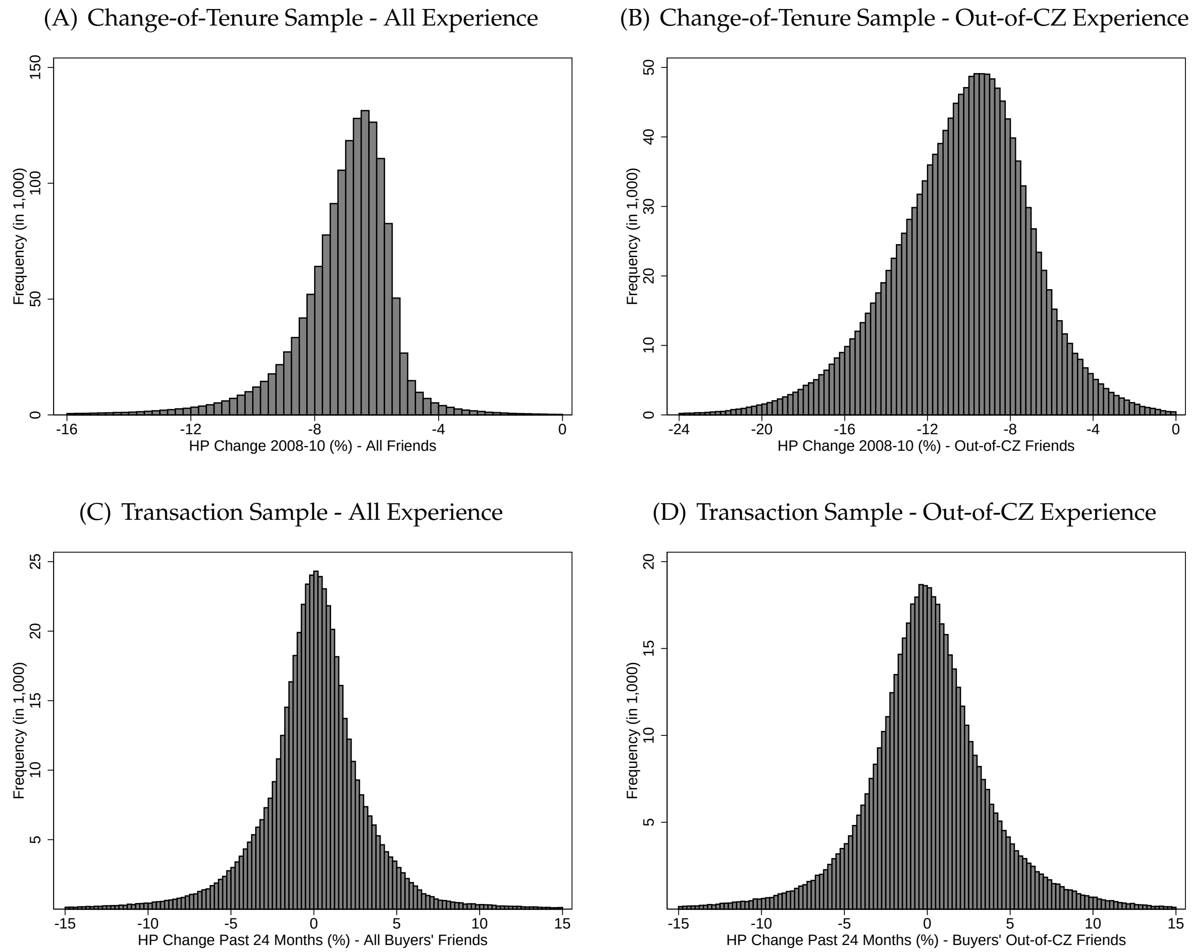
	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices Past 24 Months (%)				
Correlation < 0.5	0.464***	0.152***	0.293***	0.486***
	(0.044)	(0.017)	(0.053)	(0.017)
0.5 =< Correlation < 0.6	0.552***	0.185***	0.313***	0.457***
	(0.043)	(0.016)	(0.050)	(0.015)
Correlation >= 0.6	0.461***	0.176***	0.299***	0.445***
	(0.049)	(0.018)	(0.049)	(0.015)
Controls as in	Table 6 Column 1 2010 Renters	Table 6 Column 1 2010 Owners	Table 7 Column 1	Table 8 Column 1
P-Value (High Correlation == Low Correlation)	0.946	0.097	0.660	0.000
R-Squared	0.434	0.564	0.204	0.814
N	433,836	1,035,523	526,594	523,299

Panel B: Effects by Number of Counties in Friendship Network

	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices Past 24 Months (%)				
Below Median Number of Counties	0.605***	0.159***	0.316***	0.450***
	(0.057)	(0.019)	(0.054)	(0.015)
Above Median Number of Counties	0.616***	0.292***	0.338***	0.464***
	(0.060)	(0.028)	(0.057)	(0.016)
Controls as in	Table 6 Column 1 2010 Renters	Table 6 Column 1 2010 Owners	Table 7 Column 1	Table 8 Column 1
P-Value (Many Counties == Few Counties)	0.892	0.000	0.116	0.103
R-Squared	0.434	0.564	0.193	0.808
N	433,836	1,035,523	526,594	523,299

Note: Table shows results from the main instrumental variables regressions in Tables 6, 7, and 8. In Panel A, we analyze the effect of friends' house price experiences separately by the correlation between the house price movements in an individuals' social network and subsequent Los Angeles house price movements (see footnote 30 for details). In Panel B we analyze the effect of friends' house price experiences separately by the number of counties in which individuals have friends. Specifications and standard errors are as described in the original tables. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

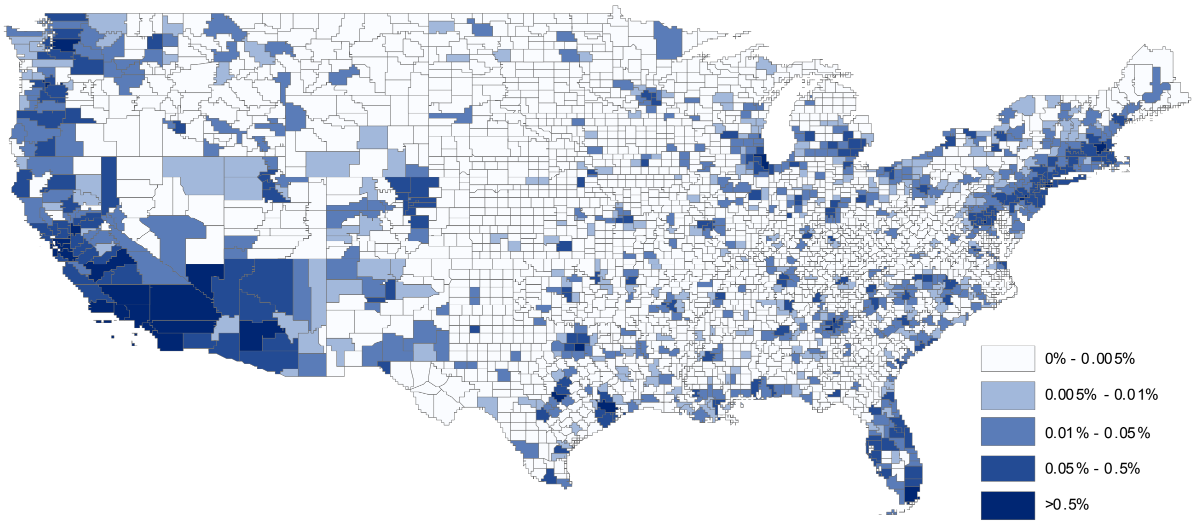
Figure 1: Distribution of Friends' House Price Experiences



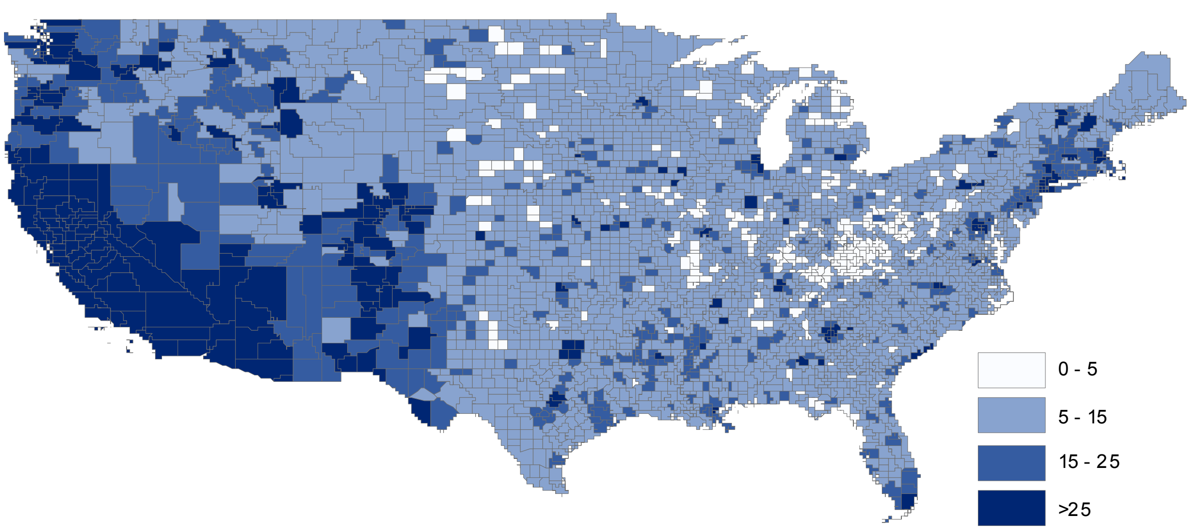
Note: Panels A and B show the distribution of the house price experiences between 2008 and 2010 of the friends of individuals in our change-of-tenure sample. See Section 1.2 for details on the sample construction. Panel A focuses on the experiences of all friends, Panel B on the experiences of out-of-commuting zone friends. Panels C and D show the distribution of the house price experiences of the friends of the buyers in our transaction sample in the 24 months prior to the transaction. Since this pools across transactions in different years, all friend experiences are shown conditional on a quarter-of-transaction fixed effect. Panel C focuses on the experiences of all friends, Panel D on the experiences of out-of-commuting zone friends. The bucket size in all Panels is 0.25 percentage points.

Figure 2: Friendship Links of Los Angeles Residents

(A) Share of Friendship Links



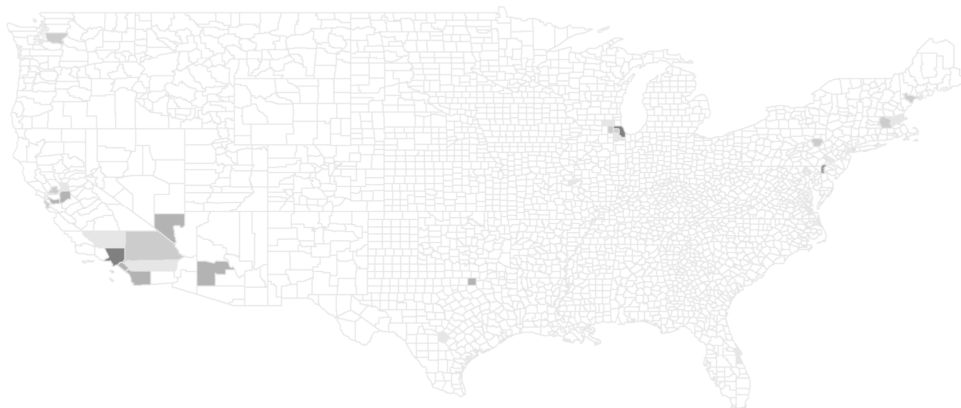
(B) Share of Friendship Links - Scaled by County FB Users



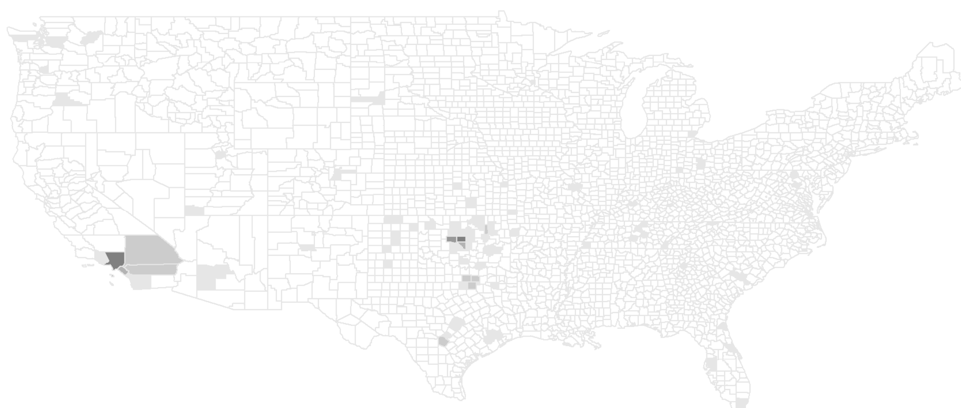
Note: Figure shows the share of U.S.-based friends of individuals in our sample that live in each county. Panel A shows the absolute share, while Panel B scales this share in each county by the number of Facebook users in that county. In other words, Panel A captures the probability that a given LA resident has a friendship link to that county, while Panel B captures the relative probability that a given Facebook user in a county has a friendship link to Los Angeles.

Figure 3: Examples of Individual-Level Friend Distributions

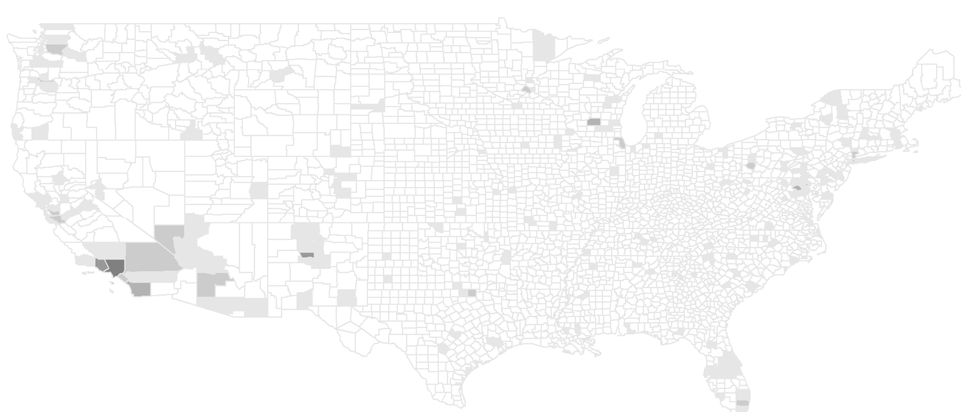
(A) Example 1 - Chicago Focus



(B) Example 2 - Oklahoma Focus

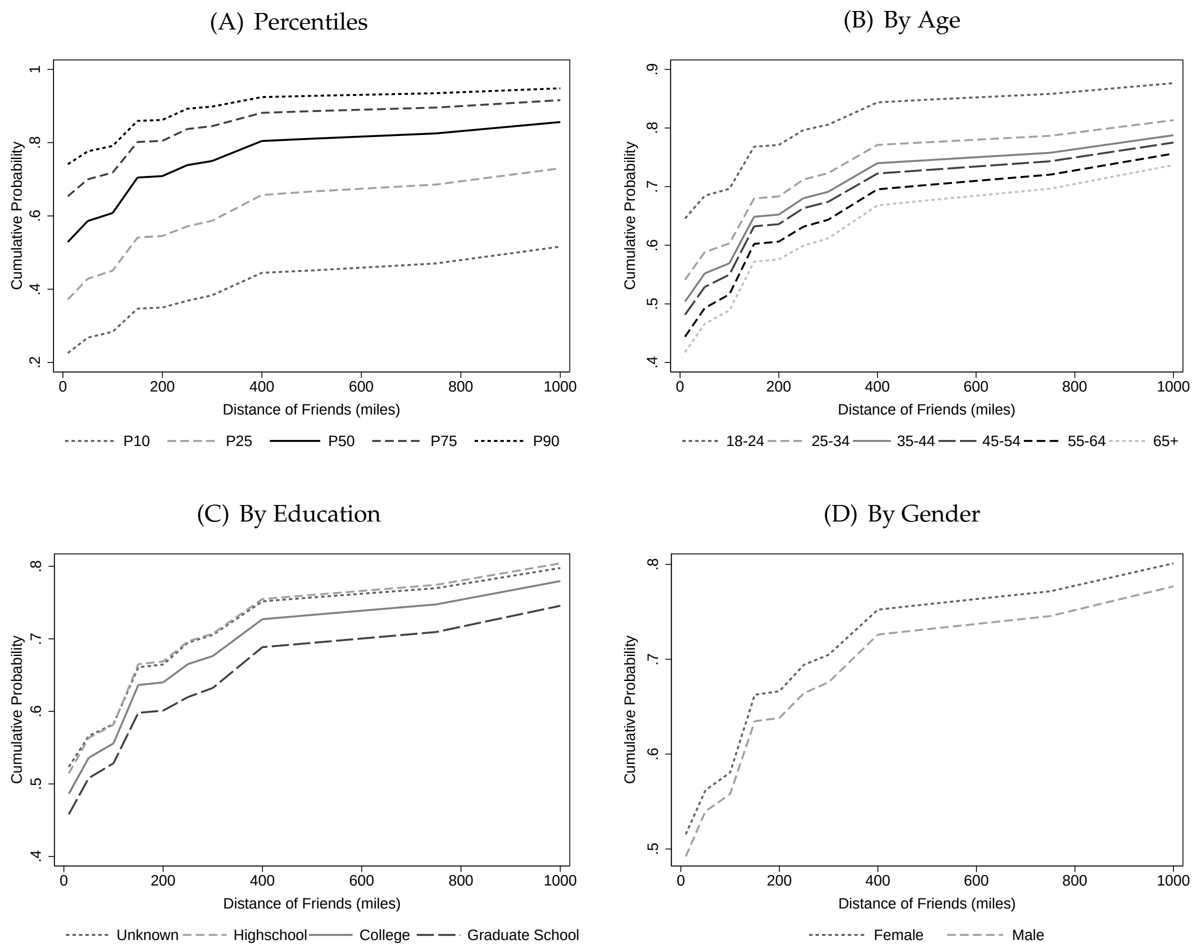


(C) Example 3 - U.S.-Wide Spread



Note: Figure shows the geographic distribution of friends of three Facebook users living as renters in Los Angeles county in 2010. Panel A shows an individual with disproportionately many friends clustered in Chicago. Panel B shows an individual with disproportionately many friends clustered in Oklahoma. Panel C shows an individual with friends in most U.S. population centers.

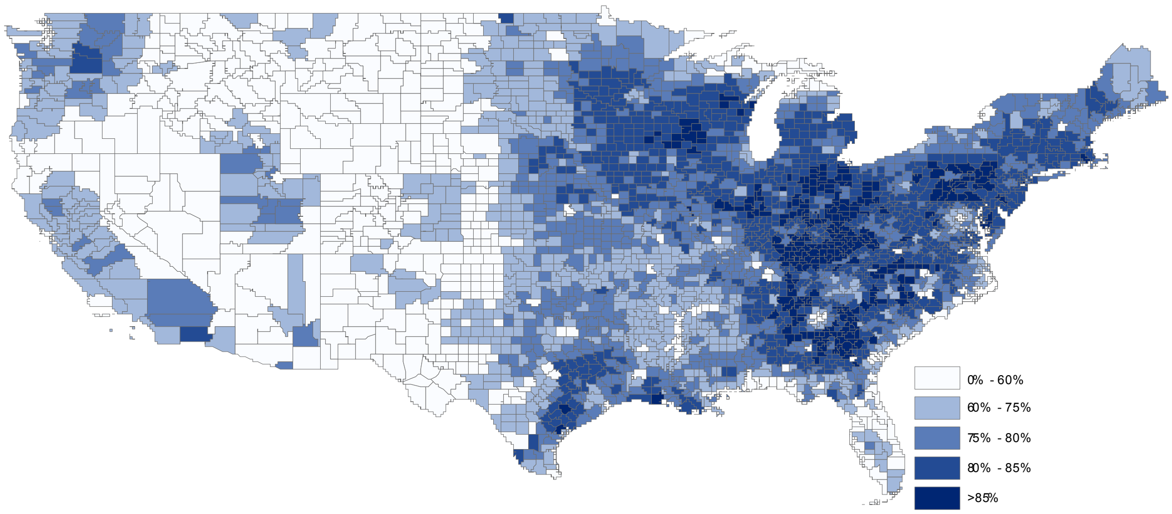
Figure 4: Geographic Spread of Social Network



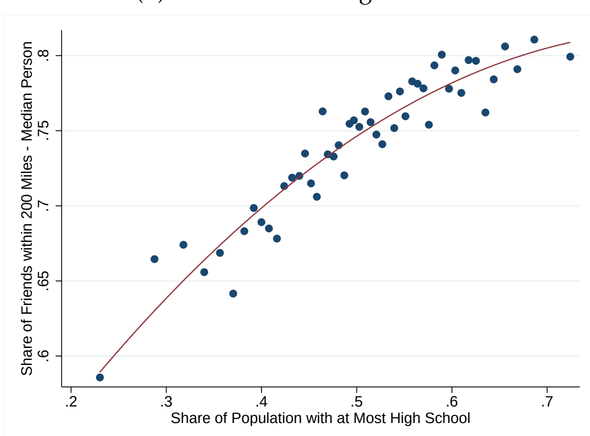
Note: Figure shows the share of U.S.-based friends of individuals in our sample that live within a certain distance of Los Angeles county. Panel A shows, for each distance, percentiles of the distribution across our population. Panels B, C, and D show averages for population groups split by age, education level, and gender, respectively.

Figure 5: Share of Friends within 200 Miles - Median Person

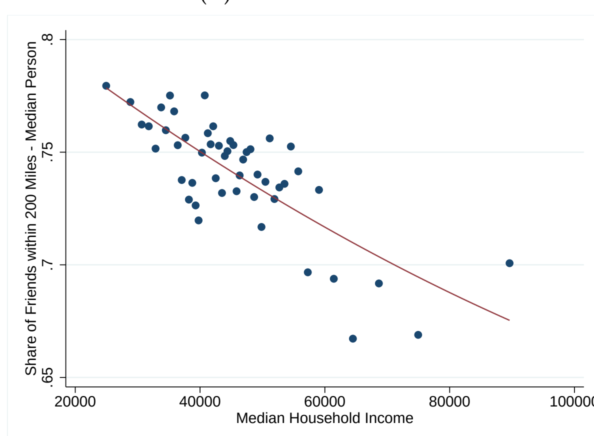
(A) Percentiles



(B) Share At Most High School



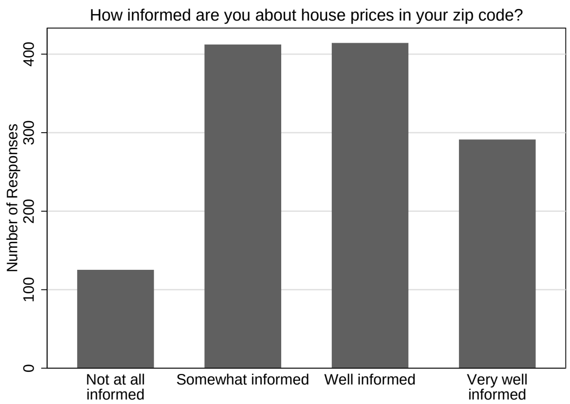
(C) Median Income



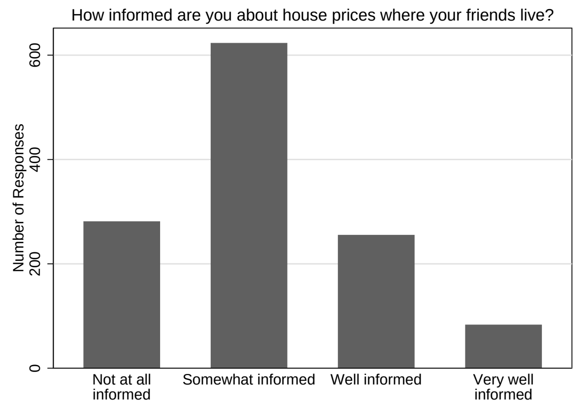
Note: Panel A shows a heat map of the share of friends living within 200 miles for the median person living in each county. Panels B and C show population-weighted binned scatter plots of the relationship between the share of friends of the median person living within 200 miles, and the share of population with at most a highschool degree and the median household income, respectively. The demographic measures come from the 2010 5-year estimates of the American Community Survey.

Figure 6: Expectations Survey

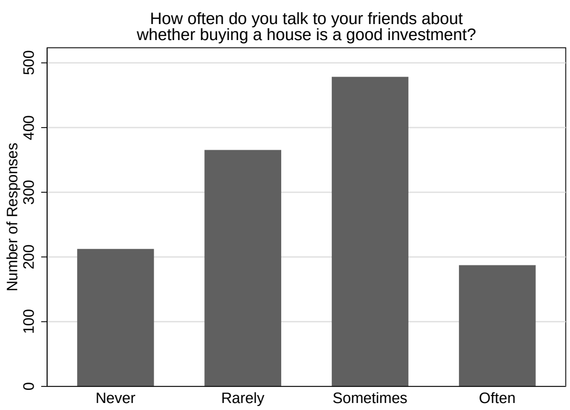
(A) Question 1



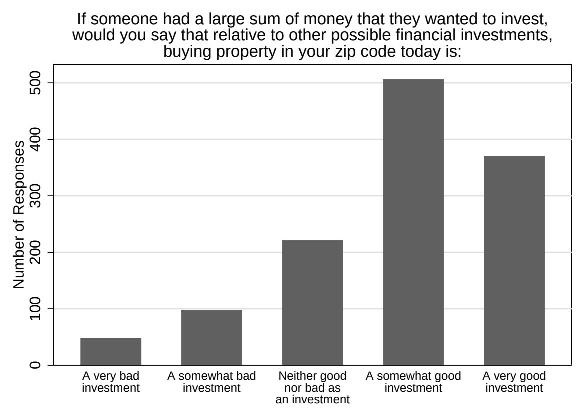
(B) Question 2



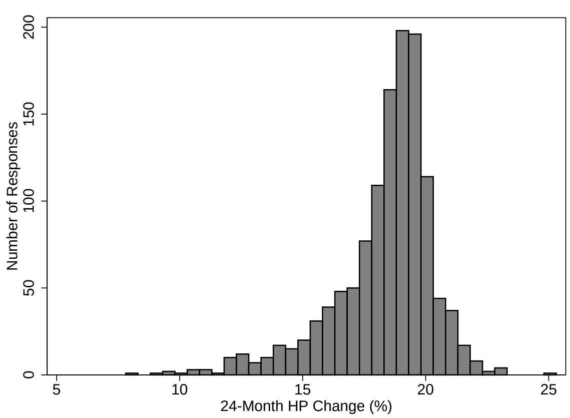
(C) Question 3



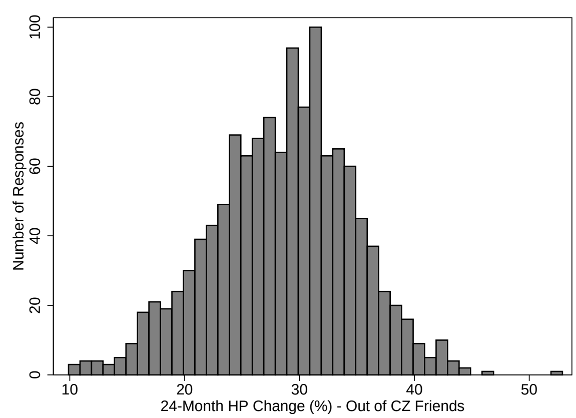
(D) Question 4



(E) All Friends



(F) Out-of-Commuting Zone Friends



Note: Panels A to D present the distribution of responses to the expectations survey conducted by Facebook in November 2015. We analyze and describe this survey in Section 4.1. Panels E and F provide the average house price experience in the survey respondents' social network in the 24 months prior to taking the survey, both for all friends, and all friends living outside the Los Angeles commuting zone.

Table A1: Summary Statistics - Change-of-Tenure Sample

	Panel A: 2010 Renters							
	Mean	SD	SD | Zip	P10	P25	P50	P75	P90
Number of Friends								
All Friends	348	454	446	55	105	212	413	747
Out-of-Commuting Zone Friends	155	277	270	17	31	68	164	359
Average Friend Appreciation 2008-10								
All Friends	-7.17%	1.93%	1.91%	-9.18%	-7.85%	-6.87%	-6.11%	-5.51%
Out-of-Commuting Zone Friends	-10.48%	3.62%	3.43%	-15.17%	-12.68%	-10.19%	-8.11%	-6.24%
Average Friend Appreciation 2010-12								
All Friends	4.27%	1.55%	1.53%	2.75%	3.85%	4.42%	4.85%	5.50%
Out-of-Commuting Zone Friends	4.46%	2.46%	2.43%	1.63%	3.19%	4.58%	5.79%	7.07%
Income 2010 (K$)	52.00	34.37	27.50	10.0	25.0	45.0	62.5	87.5
Income Change 2010-12 (K$)	2.34	28.08	27.98	-25.0	0.0	0.0	0.0	35.0
Household Size 2010	1.91	1.27	1.29	1.0	1.0	1.0	2.0	4.0
Household Size Change 2010-12	0.20	1.18	1.18	-1.0	0.0	0.0	1.0	1.0
Age 2010	37.23	13.12	13.02	24.0	29.0	36.0	45.0	55.0
Family Structure Development 2010-12								
Stayed Single	0.72	0.45	0.45	0	0	1	1	1
Got Married	0.10	0.30	0.30	0	0	0	0	0
Stayed Married	0.14	0.35	0.36	0	0	0	0	1
Got Divorced	0.04	0.19	0.19	0	0	0	0	0
Education 2010								
Has High School	0.54	0.50	0.48	0	0	1	1	1
Has College Degree	0.35	0.48	0.30	0	0	0	1	1
Has Graduate Degree	0.10	0.30	0.10	0	0	0	0	1

	Panel B: 2010 Owners							
	Mean	SD	SD | Zip	P10	P25	P50	P75	P90
Number of Friends								
All Friends	285	383	379	47	85	172	335	615
Out-of-Commuting Zone Friends	113	216	213	16	26	52	113	242
Average Friend Appreciation 2008-10								
All Friends	-7.05%	1.72%	1.69%	-8.87%	-7.68%	-6.76%	-6.06%	-5.55%
Out-of-Commuting Zone Friends	-10.28%	3.29%	3.15%	-14.48%	-12.21%	-10.02%	-8.16%	-6.49%
Average Friend Appreciation 2010-12								
All Friends	4.34%	1.34%	1.31%	3.07%	3.93%	4.43%	4.86%	5.45%
Out-of-Commuting Zone Friends	4.60%	2.31%	2.28%	1.95%	3.38%	4.68%	5.87%	7.10%
Income 2010 (K$)	77.20	41.89	33.42	25.0	45.0	62.5	112.5	150.0
Income Change 2010-12 (K$)	0.05	20.73	20.68	0.0	0.0	0.0	0.0	0.0
Household Size 2010	3.47	1.70	1.65	1.0	2.0	3.0	5.0	6.0
Household Size Change 2010-12	-0.21	1.27	1.27	-2.0	-1.0	0.0	0.0	1.0
Age 2010	42.62	15.57	15.34	25.0	32.0	43.0	54.0	63.0
Family Structure Development 2010-12								
Stayed Single	0.29	0.45	0.45	0	0	0	1	1
Got Married	0.04	0.21	0.21	0	0	0	0	0
Stayed Married	0.60	0.49	0.48	0	0	1	1	1
Got Divorced	0.07	0.25	0.25	0	0	0	0	0
Education 2010								
Has High School	0.45	0.50	0.49	0	0	0	1	1
Has College Degree	0.38	0.48	0.48	0	0	0	1	1
Has Graduate Degree	0.17	0.38	0.37	0	0	0	0	1

Note: Table shows summary statistics on the change-of-tenure regression sample used in Section 3.1. See Section 1.2 for details on the sample construction. Panel A focuses on individuals who are renting their home in 2010, Panel B on individuals who are owning their home in 2010. For each characteristic, we show the mean, standard deviation, within-zip-code standard deviation, and the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution.

Table A2: Control Variables on Purchasing Regression

	Coefficient	Standard Error
Occupation (relative to "unknown")		
Professional/Technical	1.84	0.24
Administration/Managerial	0.67	0.28
Sales/Service	0.13	0.41
Clerical/White Collar	0.10	0.18
Craftsman/Blue Collar	0.75	0.28
Student	2.00	0.47
Homemaker	0.11	0.40
Retired	0.47	0.62
Farmer	1.51	2.86
Self Employed	0.65	0.51
Educator	1.30	1.24
Legal Professional	0.32	0.57
Medical Professional	3.16	0.47
Military	-0.73	1.96
Religious	-2.57	5.58
Household Size (relative to size of 1)		
2	0.41	0.15
3	1.65	0.23
4	3.56	0.29
5	6.32	0.42
6	9.33	0.60
7	10.41	0.89
8	12.38	1.76
Change in Household Size 2010 - 2012	5.82	0.14
Change in Family Structure (rel. to "stayed married")		
Stayed Single	-1.17	0.23
Got Married	20.66	0.39
Got Divorced	8.43	0.45
Income 2010 (relative to "less than $15,000")		
$15,000 - $19,999	0.36	0.23
$20,000 - $29,999	1.12	0.19
$30,000 - $39,999	1.44	0.20
$40,000 - $49,999	2.37	0.22
$50,000 - $74,999	4.52	0.24
$75,000 - $99,999	8.26	0.37
$100,000 - $124,999	9.87	0.45
Greater than $124,999	16.61	0.64
Unknown	-8.40	1.73

	Coefficient	Standard Error
Education (relative to "unknown")		
Completed Highschool	0.46	0.15
Completed College	1.41	0.18
Completed Graduate School	3.88	0.32
Change in Income 2010 - 2012 (K$)	0.10	0.00
Number of Friends		
2nd Quintile	0.05	0.19
3rd Quintile	0.34	0.23
4th Quintile	0.54	0.28
5th Quintile	0.17	0.34
Number of Out-Of-Commuting Zone Friends		
2nd Quintile	-0.04	0.24
3rd Quintile	-0.54	0.29
4th Quintile	-0.48	0.32
5th Quintile	-0.98	0.41
Number of Counties with Friends		
2nd Quintile	-0.04	0.24
3rd Quintile	0.19	0.32
4th Quintile	0.35	0.38
5th Quintile	-0.06	0.45
Age (relative to "18-24")		
25-29	1.06	0.22
30-34	3.39	0.24
35-39	4.42	0.27
40-44	4.56	0.26
45-49	4.38	0.26
50-54	4.68	0.29
55-59	5.13	0.37
60-64	4.78	0.39
65+	6.92	0.45
Unknown	3.55	0.36

Note: Table shows coefficients and associated standard errors on the control variables in column 1 in Table 6.

Table A3: Control Variables on Property Size Regression

	Coefficient	Standard Error
Occupation in 2010 (relative to "unknown")		
Professional/Technical	3.31	0.19
Administration/Managerial	0.10	0.26
Sales/Service	-0.80	0.45
Clerical/White Collar	-0.83	0.21
Craftsman/Blue Collar	-5.76	0.26
Student	1.99	0.57
Homemaker	3.05	0.40
Retired	2.04	0.57
Farmer	8.62	2.22
Self Employed	4.58	0.50
Educator	-0.95	0.82
Legal Professional	3.01	0.50
Medical Professional	7.85	0.31
Military	-0.51	1.16
Religious	0.48	3.22
Household Size in 2010 (relative to size of 1)		
2	4.05	0.22
3	7.78	0.23
4	10.30	0.26
5	11.94	0.31
6	13.31	0.37
7	13.99	0.47
8	13.44	0.64
Education in 2010 (relative to "unknown")		
Completed Highschool	-2.49	0.19
Completed College	-1.83	0.20
Completed Graduate School	1.64	0.25
Income in 2010 (relative to "less than $15,000")		
$15,000 - $19,999	-0.49	0.51
$20,000 - $29,999	-1.62	0.43
$30,000 - $39,999	-1.30	0.44
$40,000 - $49,999	0.43	0.45
$50,000 - $74,999	3.87	0.44
$75,000 - $99,999	13.59	0.42
$100,000 - $124,999	22.04	0.38
Greater than $124,999	41.02	0.40
Unknown	17.27	2.79

	Coefficient	Standard Error
Married in 2010 (relative to "unknown")		
Single	-1.70	0.80
Married	2.47	0.78
Age at Purchase (relative to "18-24")		
25-29	-4.76	0.27
30-34	-1.33	0.24
35-39	3.21	0.27
40-44	6.42	0.25
45-49	7.13	0.28
50-54	6.62	0.32
55-59	6.67	0.40
60-64	7.45	0.53
65+	2.47	0.36
Unknown	2.55	0.26
Number of Friends		
2nd Quintile	-0.15	0.18
3rd Quintile	-0.01	0.22
4th Quintile	-0.42	0.27
5th Quintile	1.53	0.35
Number of Out-Of-Commuting Zone Friends		
2nd Quintile	-0.07	0.20
3rd Quintile	0.61	0.26
4th Quintile	2.64	0.34
5th Quintile	7.16	0.44
Number of Counties with Friends		
2nd Quintile	-0.15	0.19
3rd Quintile	0.37	0.21
4th Quintile	-0.09	0.24
5th Quintile	-2.49	0.30

Note: Table shows coefficients and associated standard errors on the control variables in column 1 in Table 7.

Table A4: Control Variables on Property Price Regression

	Coefficient	Standard Error
Property Type (rel. to "single family residence")		
Condo / Coop	-26.55	1.73
Multi-family (2-4 units)	-10.97	1.15
Multi-family (5+ units)	-22.27	1.69
Property Size (relative to smallest category)		
Category 2	22.56	1.11
Category 3	36.16	1.40
Category 4	45.92	1.54
Category 5	54.28	1.61
Category 6	62.49	1.68
Category 7	72.54	1.73
Category 8	84.59	1.86
Category 9	94.91	2.03
Category 10	103.36	2.22
Category 11	115.37	2.76
Category 12	126.31	2.98
Category 13	128.76	4.41
Category 14	123.96	4.58
Unknown	80.01	3.03
Lot Size (relative to smallest category)		
Category 2	5.28	0.70
Category 3	10.88	0.70
Category 4	16.12	0.90
Category 5	16.03	1.08
Category 6	12.52	1.42
Category 7	8.32	1.44
Category 8	5.32	1.55
Category 9	-0.27	1.91
Unknown	7.70	0.70
Has Pool	4.30	0.30
Property Age (relative to less than 5 years old)		
5-9	0.19	0.82
10-14	-0.45	1.03
15-19	-5.00	1.09
20-24	-8.81	1.14
30-34	-12.94	1.11
35-39	-14.36	1.12
40-44	-15.10	1.17
45-49	-13.16	1.28
50-54	-12.26	1.30
55-59	-10.95	1.38
60-64	-9.24	1.42
65-79	-7.14	1.44
70-74	-7.11	1.46
75-80	-6.60	1.54
80+	-7.38	1.54
Unknown	-9.76	1.49
Number of Friends		
2nd Quintile	-0.19	0.16
3rd Quintile	-0.64	0.19
4th Quintile	-1.33	0.22
5th Quintile	-2.15	0.28
Number of Out-Of-Commuting Zone Friends		
2nd Quintile	0.43	0.17
3rd Quintile	0.92	0.21
4th Quintile	1.97	0.23
5th Quintile	3.91	0.31

	Coefficient	Standard Error
Number of Counties with Friends		
2nd Quintile	0.40	0.15
3rd Quintile	0.61	0.19
4th Quintile	0.81	0.25
5th Quintile	0.87	0.28
Occupation in 2010 (relative to "unknown")		
Professional/Technical	1.58	0.17
Administration/Managerial	-0.42	0.23
Sales/Service	-0.79	0.32
Clerical/White Collar	-1.16	0.18
Craftsman/Blue Collar	-2.47	0.21
Student	0.12	0.37
Homemaker	0.08	0.32
Retired	0.04	0.52
Farmer	-2.88	1.85
Self Employed	-0.78	0.43
Educator	-0.78	0.71
Legal Professional	1.28	0.40
Medical Professional	1.71	0.25
Military	0.44	1.00
Religious	-1.61	2.13
Household Size in 2010 (relative to size of 1)		
2	0.53	0.16
3	0.04	0.17
4	-1.04	0.23
5	-1.59	0.26
6	-2.52	0.31
7	-2.44	0.37
8	-3.03	0.62
Education in 2010 (relative to "unknown")		
Completed Highschool	-0.33	0.14
Completed College	0.39	0.14
Completed Graduate School	2.19	0.19
Married in 2010 (relative to "unknown")		
Single	2.16	0.30
Married	3.13	0.33
Income in 2010 (relative to "less than $15,000")		
$15,000 - $19,999	1.06	0.45
$20,000 - $29,999	1.35	0.44
$30,000 - $39,999	1.82	0.50
$40,000 - $49,999	2.80	0.51
$50,000 - $74,999	4.86	0.55
$75,000 - $99,999	7.95	0.60
$100,000 - $124,999	10.67	0.65
Greater than $124,999	15.20	0.70
Unknown	10.25	1.50
Age at Purchase (relative to "18-24")		
25-29	0.64	0.19
30-34	1.98	0.22
35-39	2.69	0.22
40-44	2.64	0.25
45-49	2.30	0.25
50-54	2.55	0.35
55-59	2.49	0.41
60-64	3.53	0.56
65+	2.41	0.37
Unknown	0.95	0.24

Note: Table shows coefficients and associated standard errors on the control variables in column 1 in Table 8.

Table A5: Robustness Checks to Main Results

	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
Panel A: Friends from Different State	(1)	(2)	(3)	(4)
Δ Friend County House Prices	0.525***	0.161***	0.354***	0.546***
Different State Past 24 Months (%)	(0.045)	(0.018)	(0.067)	(0.018)
Controls as in	Table 6, Col1 2010 Renters	Table 6, Col1 2010 Owners	Table 7, Col1	Table 8, Col1
R-Squared	0.434	0.564	0.193	0.808
N	433,757	1,035,523	526,473	523,179
Panel B: Past 12 Month				
	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices	1.388***	0.410***	0.361***	0.501***
Past 12 Months (%)	(0.096)	(0.035)	(0.082)	(0.020)
Controls as in	Table 6, Col1 2010 Renters	Table 6, Col1 2010 Owners	Table 7, Col1	Table 8, Col1
R-Squared	0.434	0.564	0.193	0.807
N	433,836	1,035,523	493,142	520,801
Panel C: Past 36 Month				
	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices	0.232***	0.074***	0.258***	0.349***
Past 36 Months (%)	(0.082)	(0.007)	(0.035)	(0.013)
Controls as in	Table 6, Col1 2010 Renters	Table 6, Col1 2010 Owners	Table 7, Col1	Table 8, Col1
R-Squared	0.434	0.564	0.190	0.812
N	433,836	1,035,523	493,142	489,872
Panel D: Past 48 Month				
	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices	0.152***	0.048***	0.231***	0.304***
Past 48 Months (%)	(0.012)	(0.004)	(0.028)	(0.011)
Controls as in	Table 6, Col1 2010 Renters	Table 6, Col1 2010 Owners	Table 7, Col1	Table 8, Col1
R-Squared	0.434	0.564	0.190	0.812
N	433,836	1,035,523	493,142	489,872

Note: Table shows robustness of the results from the main instrumental variables regressions in Tables 6, 7, and 8. Panel A uses the house price experiences over the past 24 months of individuals' out-of-state friends, to instrument for the house price experiences of all friends. Panels B to D show our standard instrumental variables estimates where we measure friends' house price experiences over the previous 12 months, 36 months, and 48 months. Specifications and standard errors are as described in the original tables. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table A6: Differential Effects by Age

	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices Past 24 Months (%)				
Age < 30 Years	0.607***	0.353***	0.320***	0.462***
	(0.080)	(0.042)	(0.054)	(0.015)
30 Years ≤ Age < 50 Years	0.713***	0.255***	0.289***	0.443***
	(0.061)	(0.029)	(0.051)	(0.015)
Age ≥ 50 Years	0.314***	0.061***	0.345***	0.454***
	(0.091)	(0.018)	(0.054)	(0.017)
Controls	Table 6 Column 1 2010 Renters	Table 6 Column 1 2010 Owners	Table 7 Column 1	Table 8 Column 1
P-Value (High Age == Low Age)	0.017	0.000	0.141	0.371
R-Squared	0.434	0.564	0.194	0.808
N	433,836	1,035,523	526,544	523,249

Note: Table shows results from the main instrumental variables regressions in Tables 6, 7, and 8, where we analyze the effect of friends' house price experiences separately by the age of individuals. Specifications and standard errors are as described in the original tables. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table A7: Differential Effects by Education Level

	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices Past 24 Months (%)				
High School	0.514***	0.171***	0.294***	0.448***
	(0.079)	(0.027)	(0.054)	(0.015)
College	0.520***	0.149***	0.274***	0.443***
	(0.094)	(0.027)	(0.053)	(0.015)
Graduate School	0.473***	0.105***	0.286***	0.436***
	(0.185)	(0.035)	(0.055)	(0.017)
Controls	Table 6 Column 1 2010 Renters	Table 6 Column 1 2010 Owners	Table 7 Column 1	Table 8 Column 1
P-Value (High School == Graduate School)	0.845	0.145	0.527	0.113
R-Squared	0.434	0.564	0.194	0.808
N	433,836	1,035,523	526,594	523,299

Note: Table shows results from the main instrumental variables regressions in Tables 6, 7, and 8, where we analyze the effect of friends' house price experiences separately by the education level of individuals in 2010. Specifications and standard errors are as described in the original tables. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table A8: Differential Effects by Time Period

	100 x Log(Size)			100 x Log(Price)		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Friend County House Prices Past 24 Months (%)	0.364*** (0.073)	0.108** (0.042)	0.525*** (0.144)	0.404*** (0.023)	0.487** (0.018)	0.468*** (0.023)
Controls as in	Table 7, Column 1	Table 7, Column 1	Table 7, Column 1	Table 8, Column 1	Table 8, Column 1	Table 8, Column 1
Time Period	2001-2006 Boom	2007-2009 Bust	2010-2012 Flat	2001 - 2006 Boom	2007-2009 Bust	2010-2012 Flat
R-Squared	0.208	0.164	0.135	0.774	0.796	0.842
N	186,747	81,480	95,552	185,066	80,173	95,202

Note: Table shows results from the main instrumental variables regressions in Tables 7 and 8, separately for three different time periods: 2001-2006, a period where Los Angeles house prices were going up; 2007-2009, a period when Los Angeles house prices were going down; and 2010-2012, a period when Los Angeles house prices were relatively flat. Specifications and standard errors are as described in the original tables. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table A9: Expectation Whether Buying Property is a Good Investment

	(1)	(2)	(3)	(4)	(5)
Δ Friend County House Prices 2013-2015 (%)	1.075**	1.067**			
	(0.032)	(0.038)			
Δ Friend County House Prices 2013-2015 (%) x Ordering of Question					
Expectation Question Last			1.069**		
			(0.032)		
Expectation Question First			1.091**		
			(0.034)		
Δ Friend County House Prices 2013-2015 (%) x Knowledge of HP in Friends' Location					
Not at all informed				1.008	
				(0.061)	
Somewhat informed				1.086	
				(0.056)	
Well informed				1.099*	
				(0.078)	
Very well informed				1.216*	
				(0.173)	
Δ Friend County House Prices 2013-2015 (%) x Talk with Friend about Housing Investment					
Never					0.959
					(0.057)
Rarely					1.013
					(0.048)
Sometimes					1.130***
					(0.053)
Often					1.253**
					(0.144)
Demographic Controls	Y	Y	Y	Y	Y
Zip Code Fixed Effects	Y	Y	Y	Y	Y
Sample		LA in 2012			
N	1,242	1,110	1,242	1,242	1,242

Note: Table shows results from a conditional ordered logit estimation of regression 8. The dependent variable is the answer to survey Question 4: "If someone had a large sum of money that they wanted to invest, would you say that relative to other possible financial investments, buying property in your zip code today is: (1) A very bad investment, (2) A somewhat bad investment, (3) Neither good nor bad as an investment, (4) A somewhat good investment, or (5) A very good investment, with the 5 (ordered) answers recoded to 1-5. Column 1 shows the baseline estimates. Column 2 restricts the sample to respondents who lived in LA in 2012. The last three columns estimate differential effects by the ordering of the questions (column 3), by how informed respondents claimed to be about their friends' house price experiences (column 4), and by how often respondents report talking to their friends about whether buying property is a good investment (column 5). The specifications in columns 3, 4, and 5, also include non-interacted indicator variables for the question ordering, and the possible responses to Questions 2 and 3, respectively; in the interest of space, the corresponding coefficients are not reported. All columns also control for respondent age and gender. Standard errors are in parentheses. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table A10: Differential Effects by Type of Social Network

Panel A: Family Network

	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices	0.627***	0.243***	0.355***	0.430***
Past 24 Months (%)	(0.120)	(0.048)	(0.075)	(0.035)
Controls as in	Table 6 Column 1 2010 Renters	Table 6 Column 1 2010 Owners	Table 7 Column 1	Table 8 Column 1
R-Squared	0.470	0.602	0.197	0.809
N	266,882	597,903	320,777	319,059

Panel B: Same College Network

	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices	0.645***	0.266***	0.515***	0.429***
Past 24 Months (%)	(0.151)	(0.062)	(0.101)	(0.046)
Controls as in	Table 6 Column 1 2010 Renters	Table 6 Column 1 2010 Owners	Table 7 Column 1	Table 8 Column 1
R-Squared	0.513	0.652	0.213	0.816
N	131,371	303,393	161,788	160,423

Panel C: Same Employer Network

	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices	0.940***	0.428***	0.311***	0.383***
Past 24 Months (%)	(0.261)	(0.115)	(0.137)	(0.062)
Controls as in	Table 6 Column 1 2010 Renters	Table 6 Column 1 2010 Owners	Table 7 Column 1	Table 8 Column 1
R-Squared	0.560	0.711	0.207	0.822
N	83,041	177,207	122,755	121,918

Note: Table shows robustness of the results from the main instrumental variables regressions in Tables 6, 7, and 8, when we instrument for the overall house price experiences within an individual's social network with the experience of three subsets of their out-of-commuting zone friends: members of their family (Panel A), individuals who went to the same college (Panel B), and individuals who have the same employer (Panel C). Not all individuals link their family members, or report their college and employer, so the sample sizes are smaller than in the baseline regressions. Specifications and standard errors are as described in the original tables. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table A11: Robustness Checks with Sample Restrictions on Hometown

	Panel A - Hometown Los Angeles			
	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices	1.195***	0.285***	0.407***	0.543***
Past 24 Months (%)	(0.106)	(0.033)	(0.100)	(0.028)
Controls as in	Table 6 Column 1 2010 Renters	Table 6 Column 1 2010 Owners	Table 7 Column 1	Table 8 Column 1
R-Squared	0.435	0.610	0.185	0.803
N	143,768	374,733	166,118	165,469
	Panel B - Hometown Outside U.S.			
	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices	0.424***	0.178***	0.484***	0.498***
Past 24 Months (%)	(0.094)	(0.038)	(0.081)	(0.033)
Controls as in	Table 6 Column 1 2010 Renters	Table 6 Column 1 2010 Owners	Table 7 Column 1	Table 8 Column 1
R-Squared	0.481	0.622	0.178	0.841
N	63,998	122,115	74,300	74,006

Note: Table shows robustness of the results from the main instrumental variables regressions in Tables 6, 7, and 8, when we restrict the sample to individuals whose hometown is Los Angeles (Panel A), and when we restrict the sample to individuals whose hometown is outside the United States (Panel B). Specifications and standard errors are as described in the original tables. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

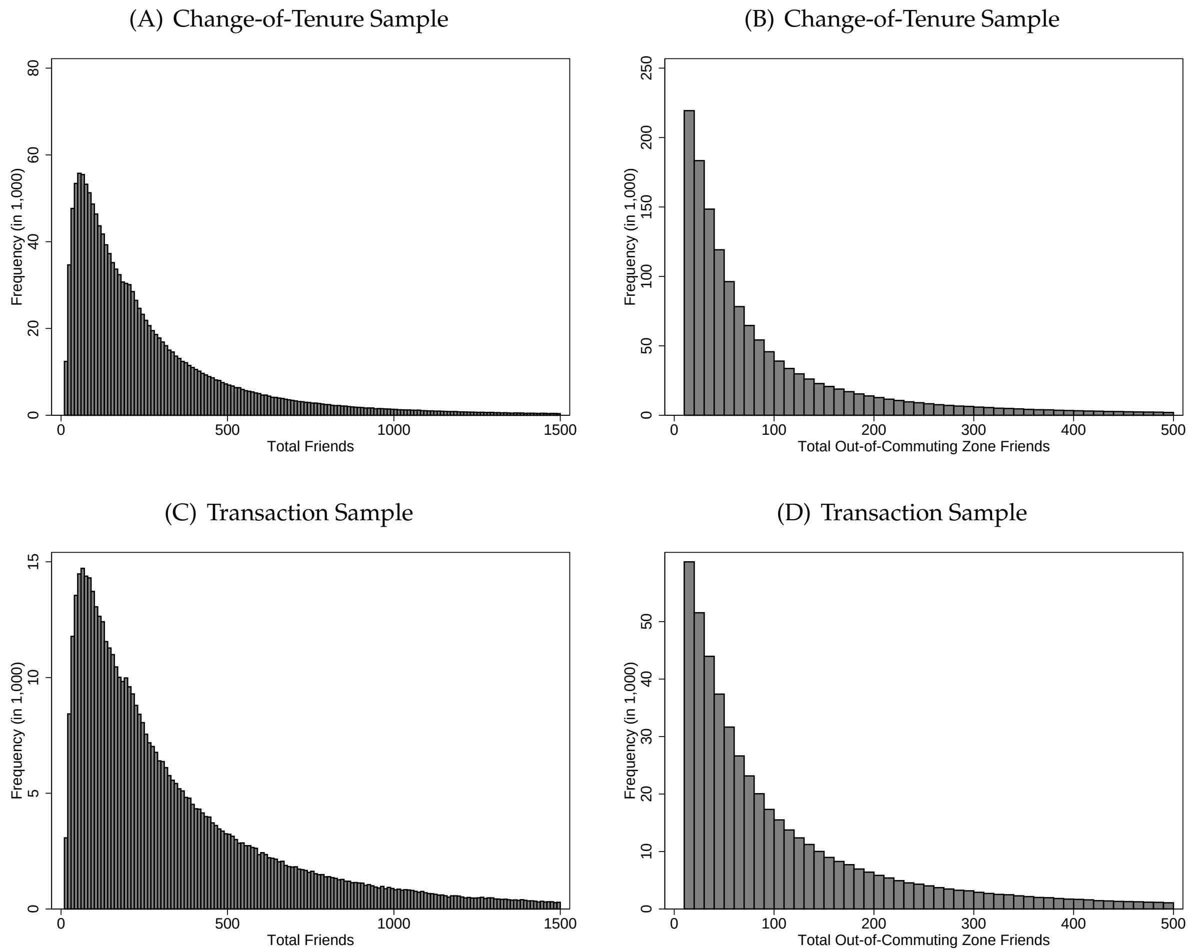
Table A12: Robustness Checks with Trading Volume Controls

	Panel A: Control for Change of Trading Volume			
	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices Past 24 Months (%)	0.621***	0.199***	0.267***	0.460***
	(0.043)	(0.015)	(0.049)	(0.016)
Friend County Housing Trading Volume				
Δ Change Last 24 Months (%)	0.002	-0.000	-0.008**	0.009***
	(0.002)	(0.001)	(0.003)	(0.001)
Controls as in	Table 6	Table 6	Table 7	Table 8
	Column 1	Column 1	Column 1	Column 1
	2010 Renters	2010 Owners		
R-Squared	0.434	0.564	0.176	0.800
N	433,813	1,035,495	389,504	386,238

	Panel B: Control for Change and Level of Trading Volume			
	P(Own in 2012)		100 x Log(Size)	100 x Log(Price)
	(1)	(2)	(3)	(4)
Δ Friend County House Prices Past 24 Months (%)	0.519***	0.177***	0.267***	0.464***
	(0.047)	(0.017)	(0.049)	(0.015)
Friend County Housing Trading Volume				
Δ Change Last 24 Months (%)	0.010***	0.001*	-0.008**	0.020***
	(0.002)	(0.001)	(0.003)	(0.002)
Level	-0.011***	-0.002***	0.002**	-0.021***
	(0.001)	(0.001)	(0.002)	(0.002)
Controls as in	Table 6	Table 6	Table 7	Table 8
	Column 1	Column 1	Column 1	Column 1
	2010 Renters	2010 Owners		
R-Squared	0.434	0.564	0.176	0.801
N	433,813	1,035,495	389,504	386,238

Note: Table shows robustness of the results from the main instrumental variables regressions in Tables 6, 7, and 8, when we also include average county trading volume and its changes over the past 24 months for all members of individuals' social networks as control variables. This trading volume is measured as the fraction of the housing stock that transacts every year. Specifications and standard errors are as described in the original tables. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

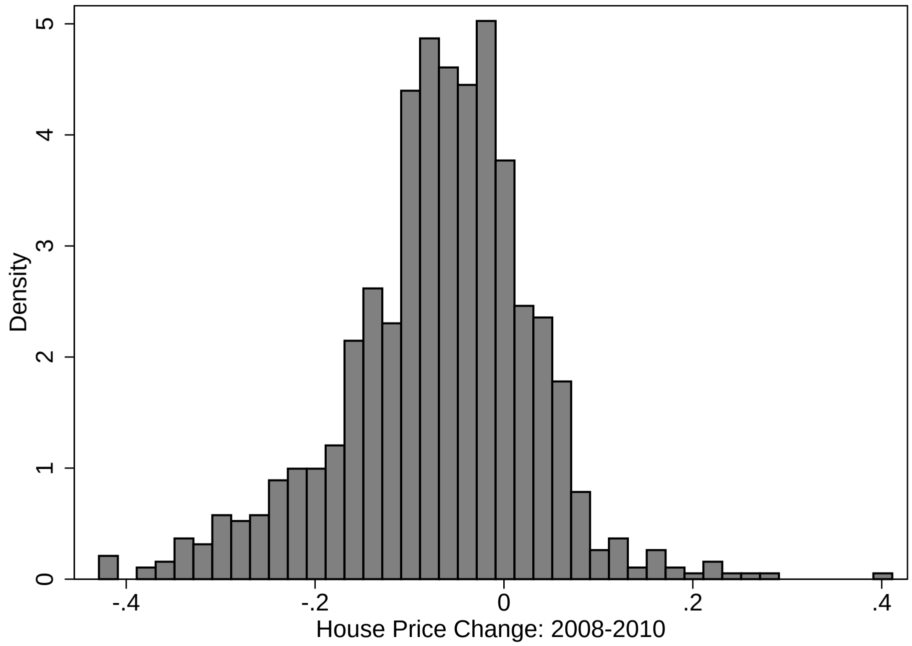
Figure A1: Distribution of Number of Friends



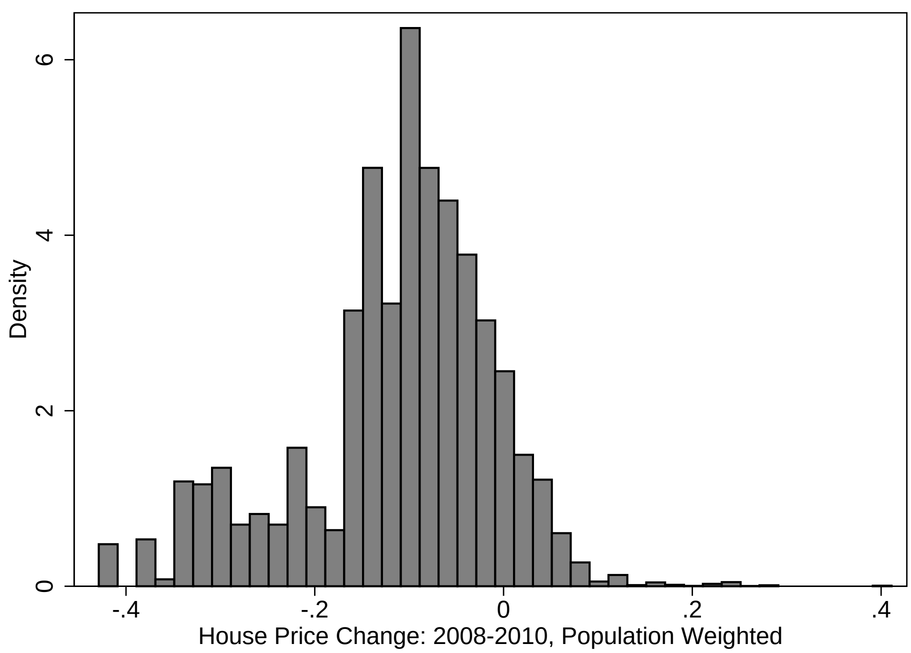
Note: Figure plots the distribution of the total number of Facebook friends (left column) and the total number of out-of-commuting zone friends (right column) for the change-of-tenure sample used in Section 3.1 (top row) and the transaction sample used in Sections 3.2 and 3.3. All samples are described in Section 1.2. The bucket size in all Panels is 10 friends.

Figure A2: Across-County House Price Movements: 2008-2010

(A) Counties - Equal Weighted

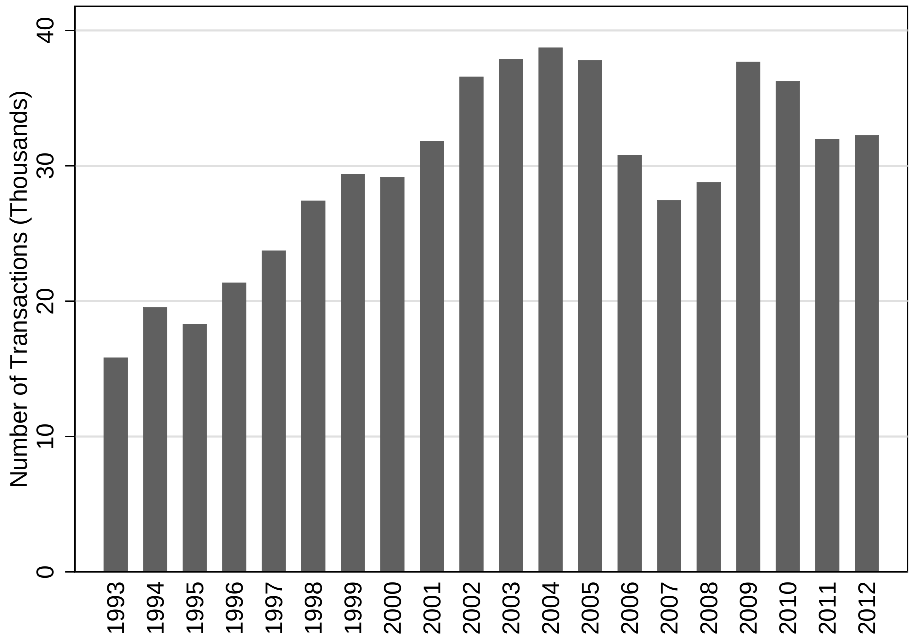


(B) Counties - Population Weighted



Note: Figure shows the distributions across counties of the house price movements between 2008 and 2010. Panel A weights each county equally, Panel B weights counties by their population.

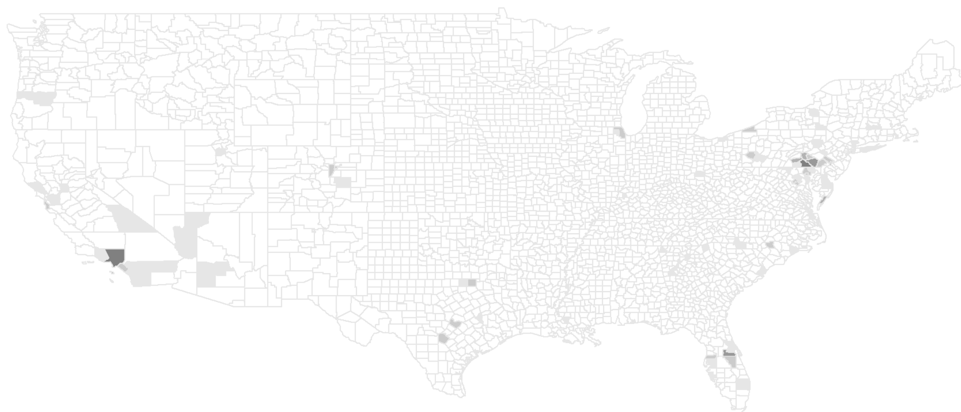
Figure A3: Number of Transactions by Year



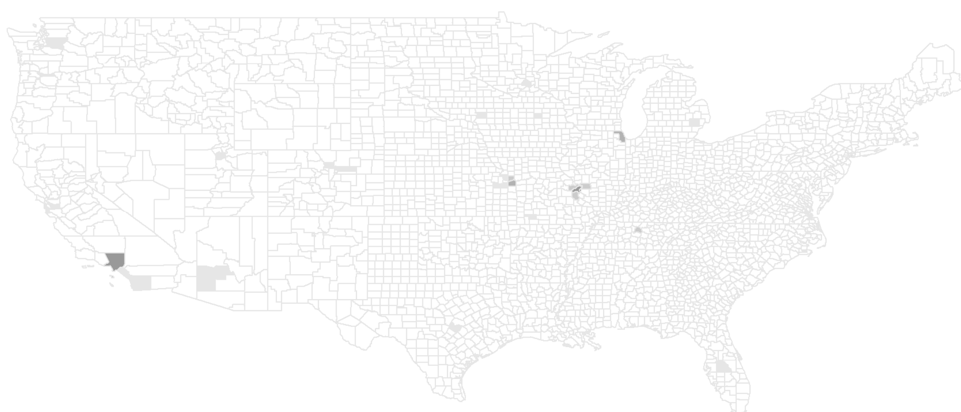
Note: Figure shows the distributions of transactions across years in the transaction sample.

Figure A4: Examples of Individual-Level Friend Distributions

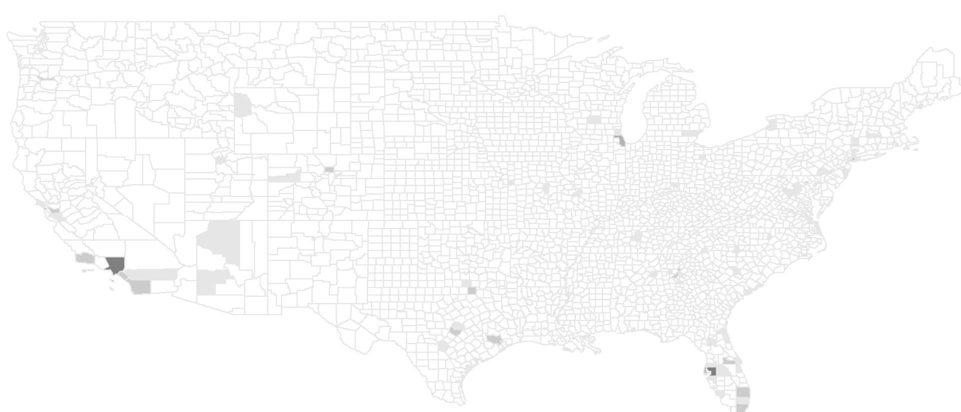
(A) Example 1 - Pennsylvania Focus



(B) Example 2 - Missouri Focus



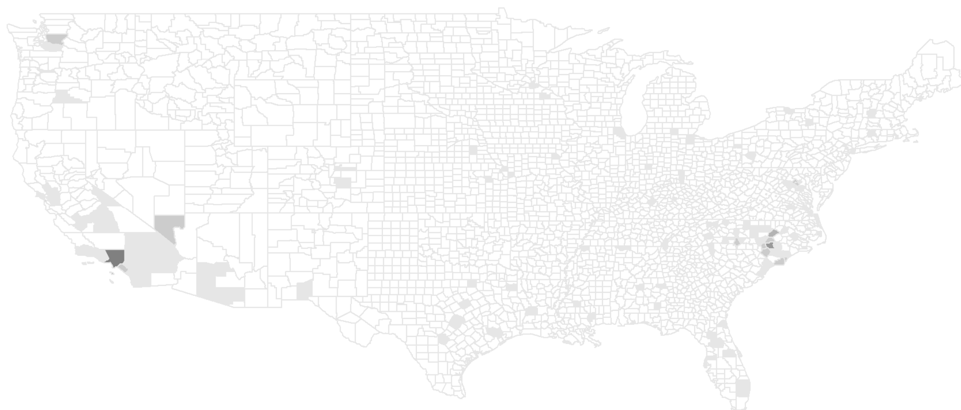
(C) Example 3 - Florida Focus



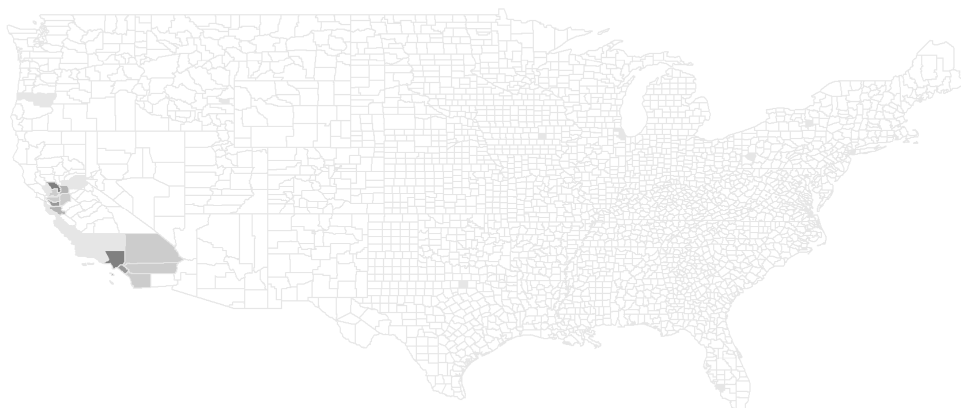
Note: Figure shows the geographic distribution of friends for three different individuals living in Los Angeles County in 2010. The friendship networks for these three individuals are clustered in Pennsylvania, Missouri, and Florida, as shown in Panels A, B, and C, respectively.

Figure A5: Examples of Individual-Level Friend Distributions

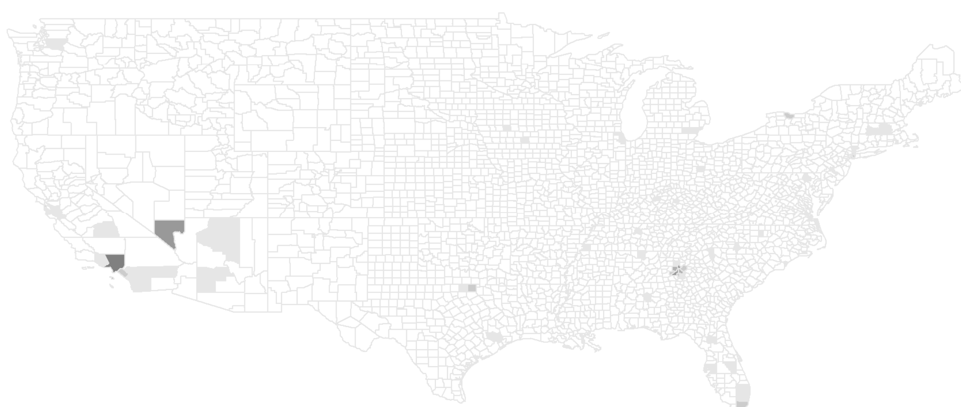
(A) Example 1 - North Carolina Focus



(B) Example 2 - Bay Area Focus

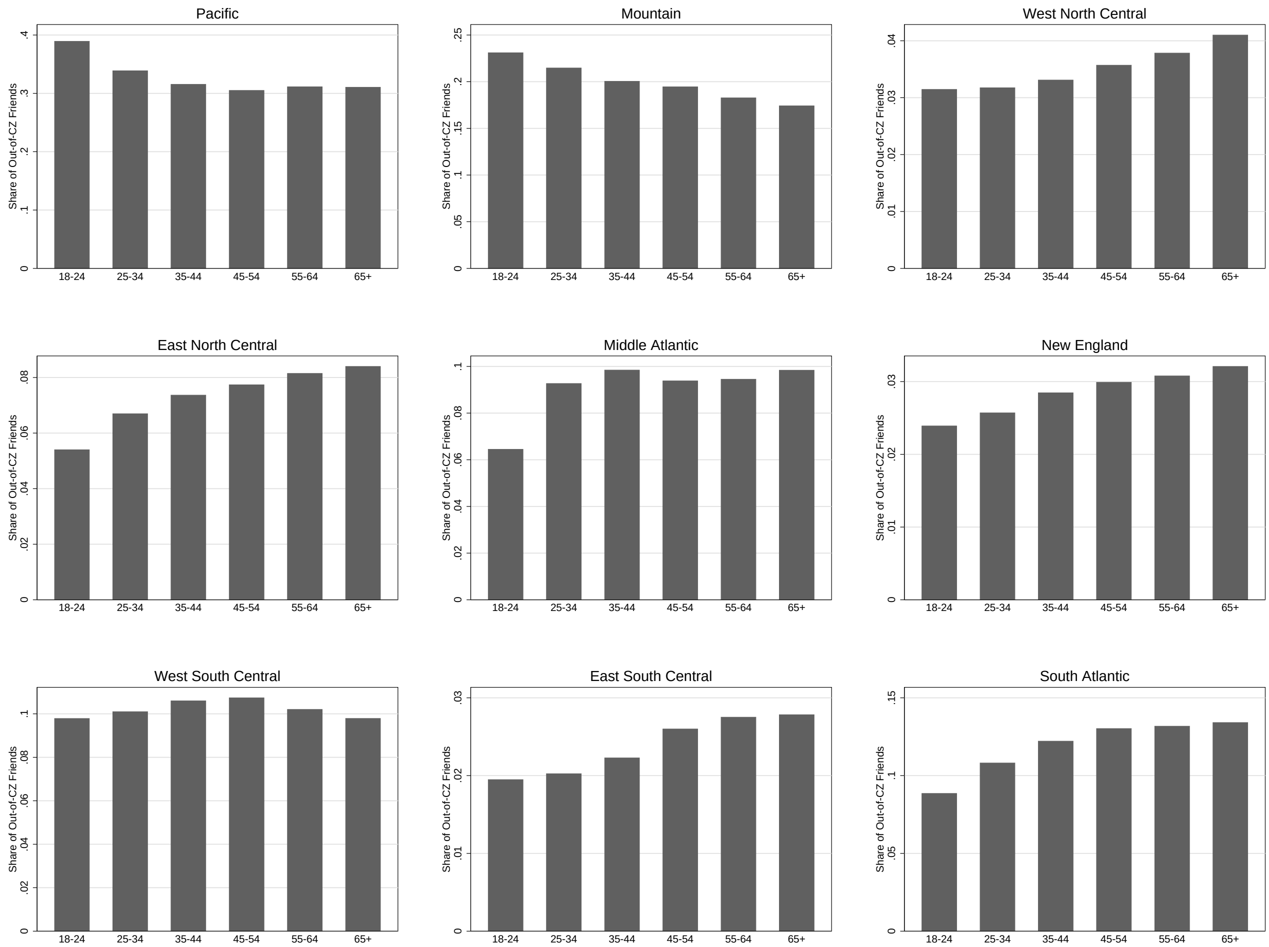


(C) Example 3 - Nevada & Georgia Focus



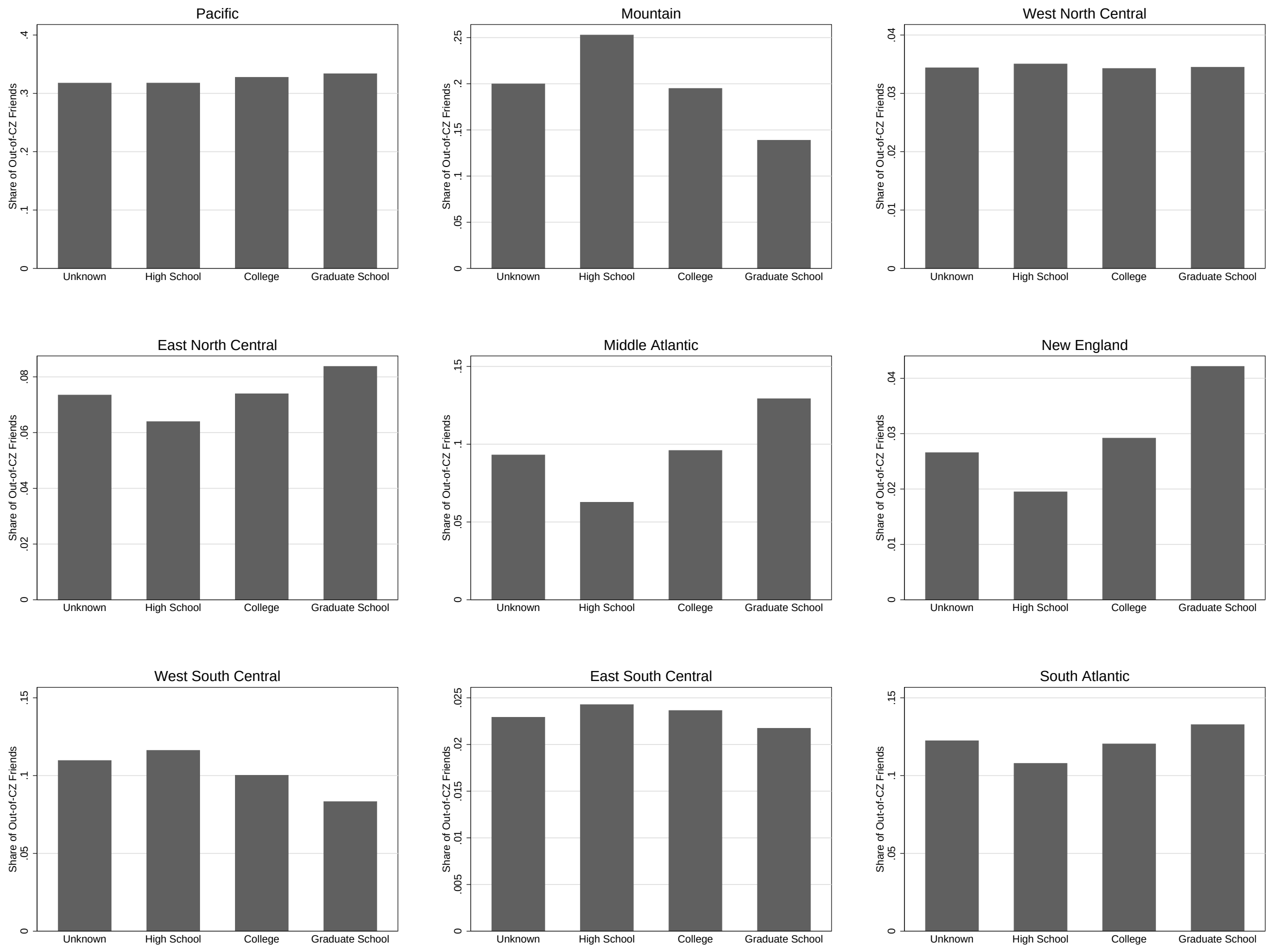
Note: Figure shows the geographic distribution of friends for three different individuals living in Los Angeles County in 2010. The friendship networks for these three individuals are clustered in North Carolina, the Bay Area, and Nevada/Georgia, as shown in Panels A, B, and C, respectively.

Figure A6: Census Division of Out-of-Commuting Zone Friends By Age



Note: Figure shows the share of the U.S.-based out-of-commuting zone friends of individuals in our sample that live in each of the nine census divisions, separately by the age of the individual.

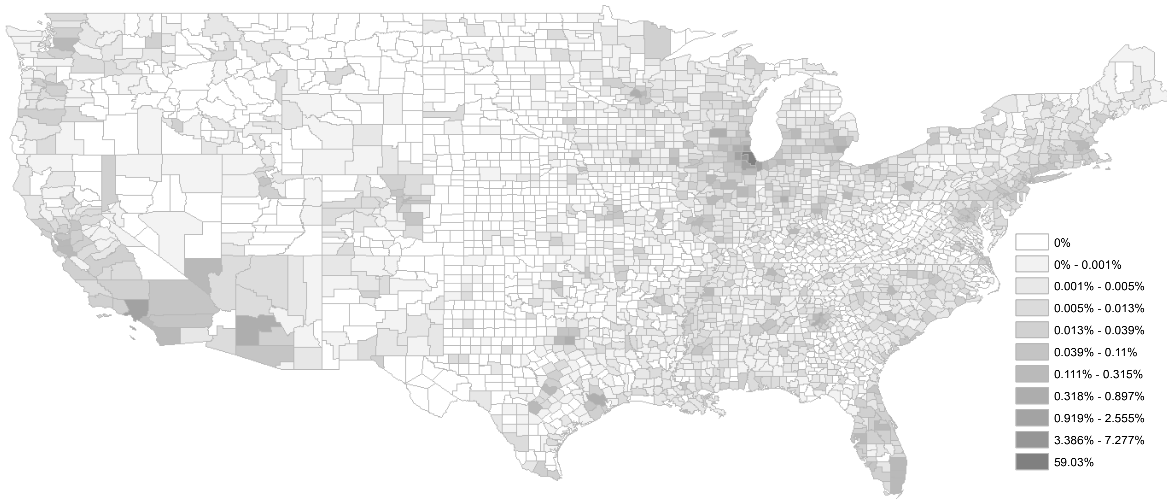
Figure A7: Census Division of Out-of-Commuting Zone Friends By Education



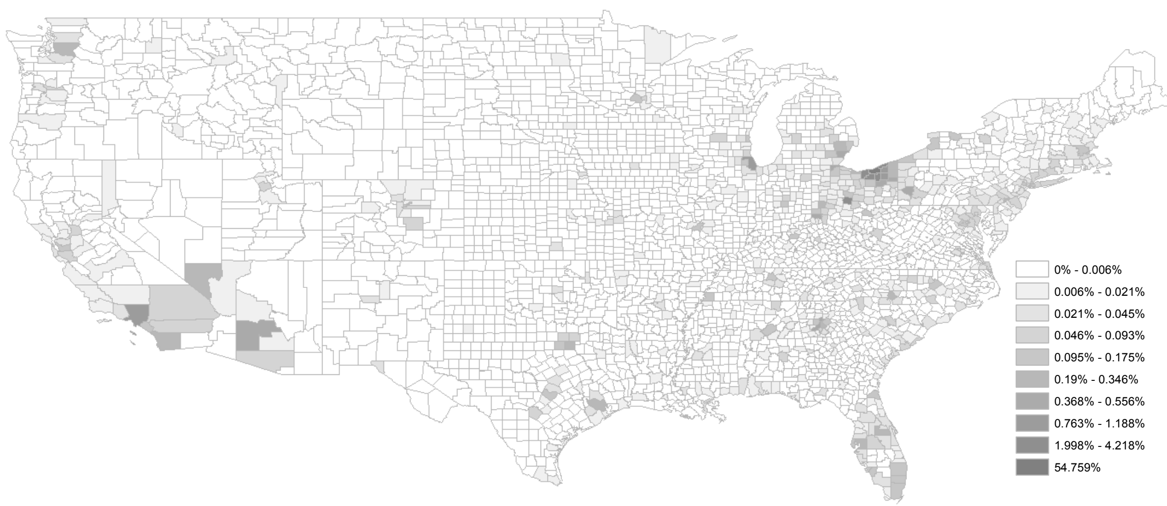
Note: Figure shows the share of the U.S.-based out-of-commuting zone friends of individuals in our sample that live in each of the nine census divisions, separately by the education level of the individual.

Figure A8: Examples of County-Level Friend Distributions

(A) Example 1 - Cook County, IL (Chicago)



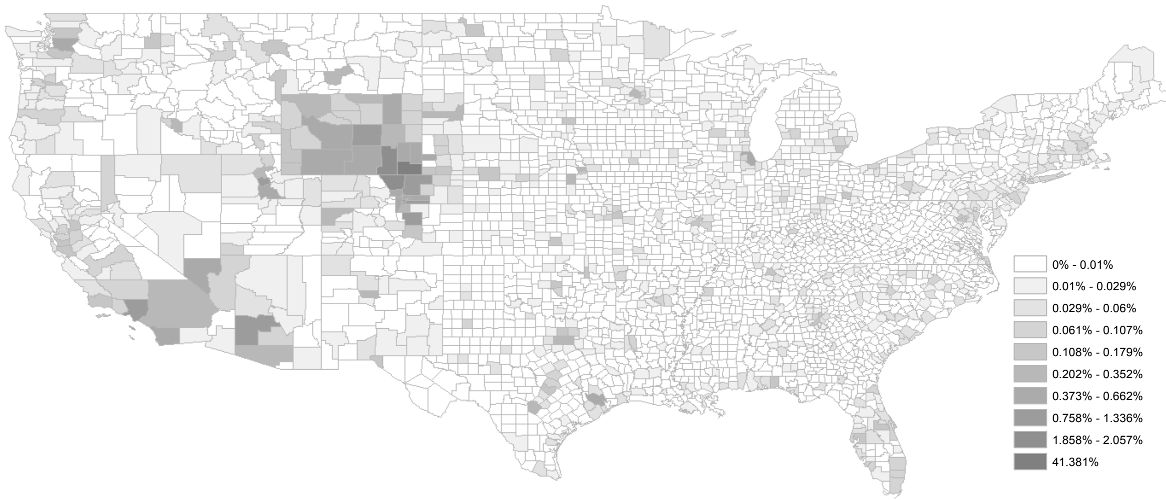
(B) Example 2 - Cuyahoga County, OH (Cleveland)



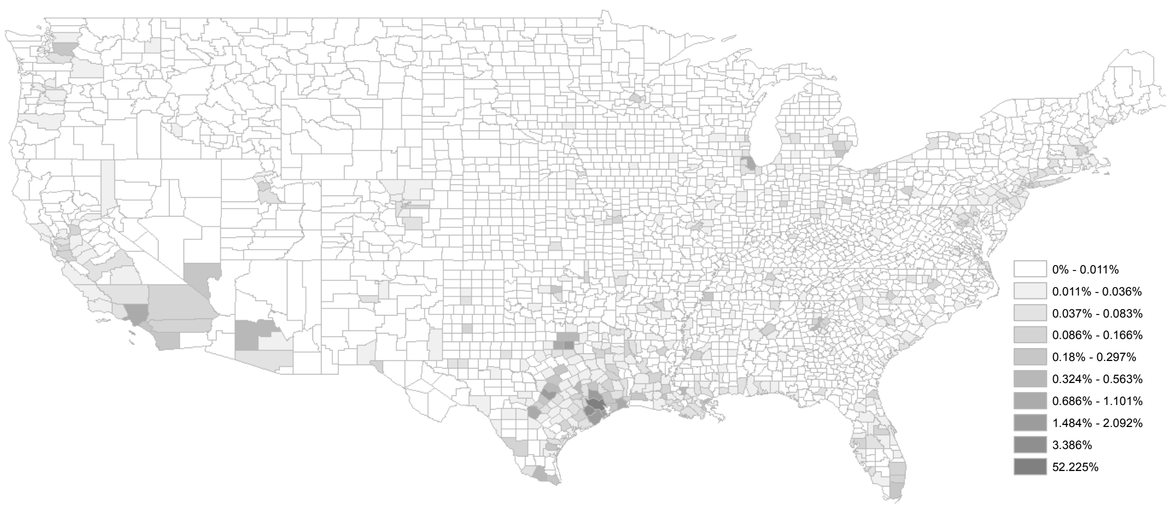
Note: Figure shows the geographical distribution of friends for all individuals living in Cook County, IL (Chicago) and Cuyahoga County, OH (Cleveland).

Figure A9: Examples of County-Level Friend Distributions

(A) Example 1 - Laramie County, WY



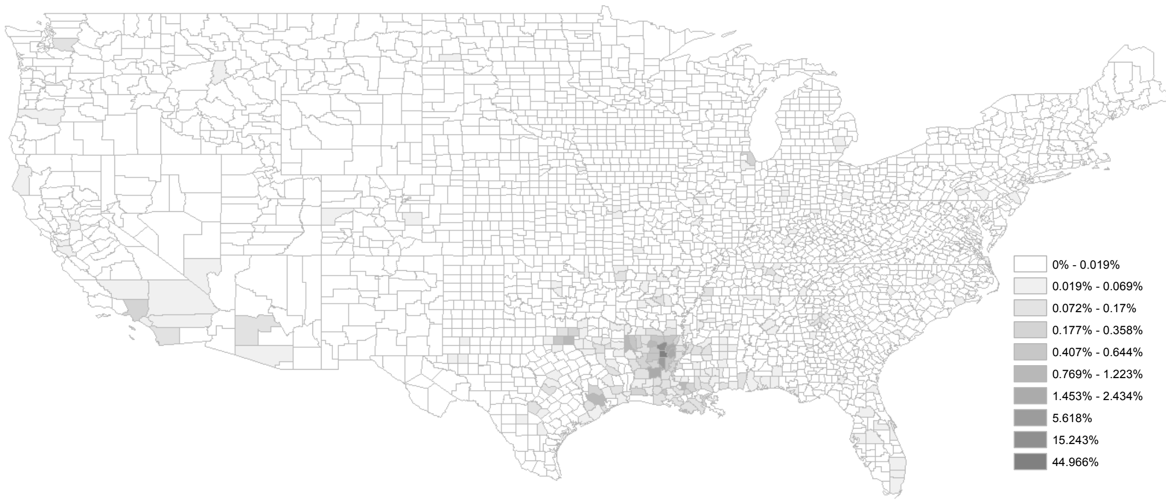
(B) Example 2 - Harris County, TX (Houston)



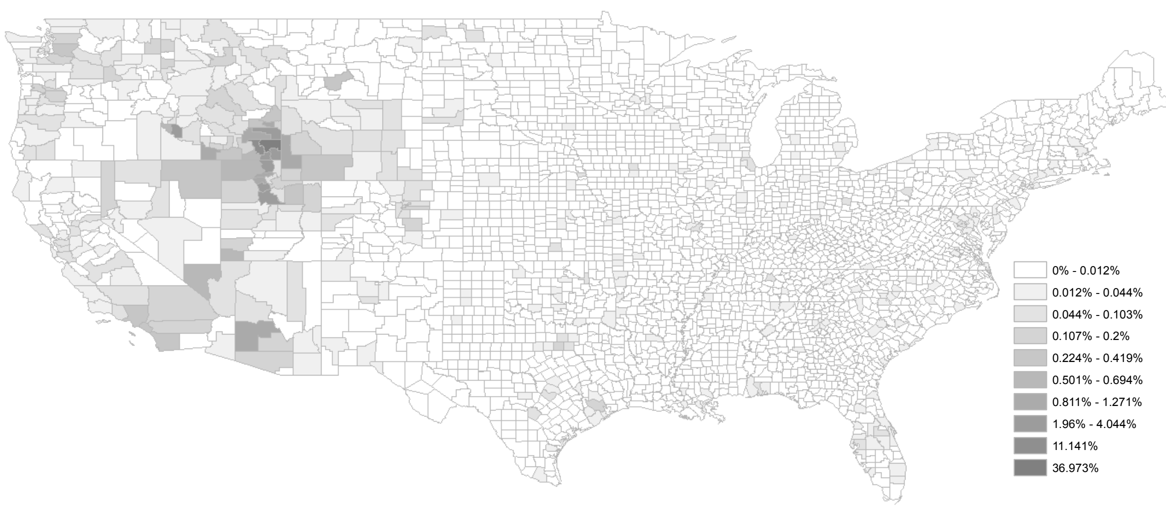
Note: Figure shows the geographical distribution of friends for all individuals living in Laramie County, WY and Harris County, TX (Houston).

Figure A10: Examples of County-Level Friend Distributions

(A) Example 1 - Caldwell County, LA

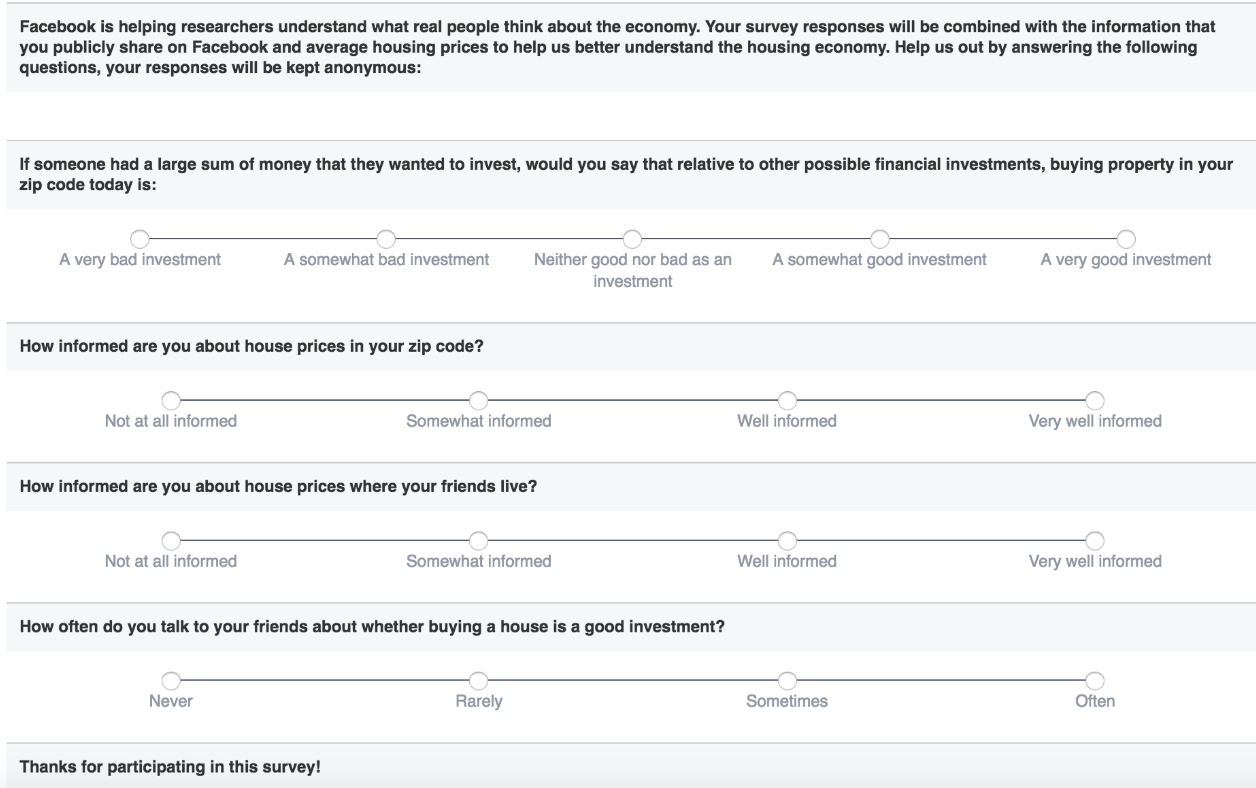


(B) Example 2 - Caribou County, ID



Note: Figure shows the geographical distribution of friends for all individuals living in Caldwell County, LA, and Caribou County, ID.

Figure A11: Interface of Expectations Survey



Facebook is helping researchers understand what real people think about the economy. Your survey responses will be combined with the information that you publicly share on Facebook and average housing prices to help us better understand the housing economy. Help us out by answering the following questions, your responses will be kept anonymous:

If someone had a large sum of money that they wanted to invest, would you say that relative to other possible financial investments, buying property in your zip code today is:

A very bad investment | A somewhat bad investment | Neither good nor bad as an investment | A somewhat good investment | A very good investment

How informed are you about house prices in your zip code?

Not at all informed | Somewhat informed | Well informed | Very well informed

How informed are you about house prices where your friends live?

Not at all informed | Somewhat informed | Well informed | Very well informed

How often do you talk to your friends about whether buying a house is a good investment?

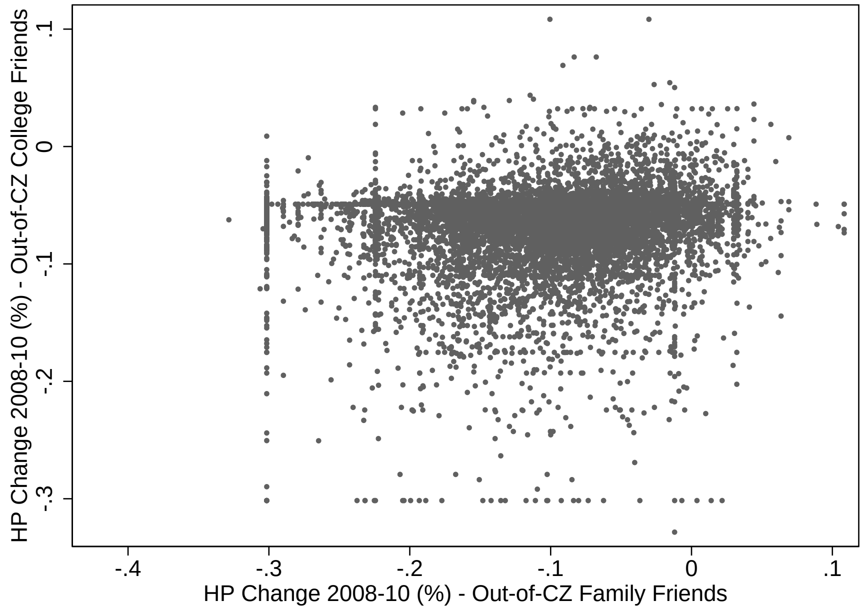
Never | Rarely | Sometimes | Often

Thanks for participating in this survey!

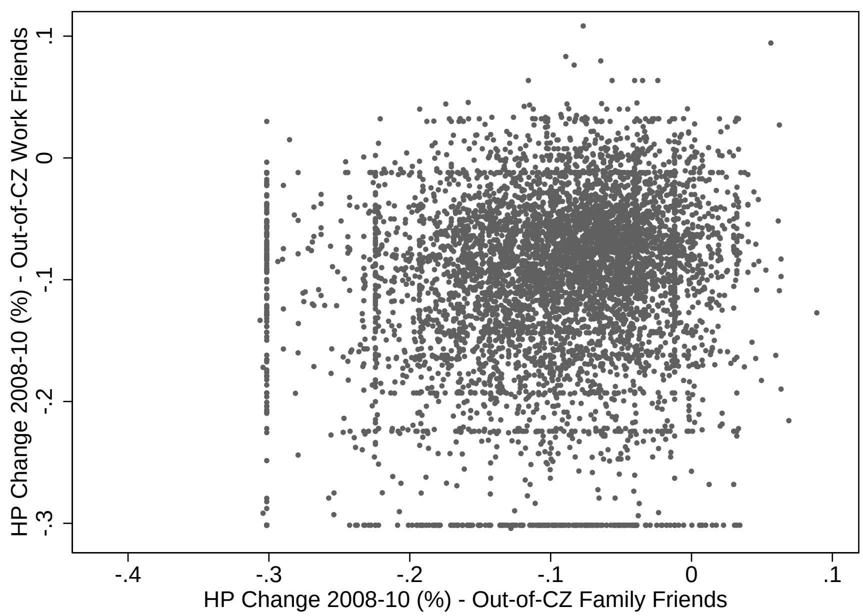
Note: Figure shows the graphical interface of the survey conducted by Facebook. We analyze the results of this survey in Section 4.1.

Figure A12: Correlation Between Experiences in Different Networks

(A) Family Friends vs. College Friends



(B) Family Friends vs. Work Friends



Note: Figure shows the correlation between the 2008-2010 house price experiences of out-of-commuting zone family members and out-of-commuting zone college friends (Panel A), and between of out-of-commuting zone family members and out-of-commuting zone work friends (Panel B).