Did Social Interactions Fuel or Suppress the US Housing Bubble?*

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Abstract

We study the implications of social interactions for financial markets in which investors exhibit different degrees of sophistication and can influence each other's beliefs through their interaction. We show that social interactions can either increase or decrease the likelihood for a financial bubble, depending on whether unsophisticated or sophisticated investors have greater social influence. We also present empirical evidence consistent with the theoretical framework from the recent housing bubble. We find that sociability promotes more conservative demand for housing and more stable real estate prices, particularly when the number of sophisticated residents in an area is high.

Keywords: **Contagion, Bubbles, Real Estate, Financial Literacy, Subprime Mortgages**

JEL Classification: D1, G12, G21

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1 Introduction

A growing literature in finance and economics has argued that individual investment decisions are significantly influenced by social interactions. Although social factors could affect investors through various channels, such as information, fashion, and quest for status, researchers tend to agree that the equilibria under social influence are not Pareto-efficient and are characterized with excessive participation rates (Dupor and Liu 2003) and abnormal risk-taking (Abel 1990, Chan and Kogan 2002, Roussanov 2010). There is also a predominant understanding in the literature that social influence can propagate asset-pricing bubbles through contagion by drawing new investors into ascending markets, thus further fueling demand and prices.[1] Not surprisingly, social influence in financial markets has been often characterized with the terms "herding," "irrational exuberance," and "mania".

The negative views on social interactions in economics contrast with the views in other social disciplines. Many social scientists currently accept the view that socialization is the most influential learning process one can experience (Bandura 1977, Wertsch 1991). People rely on the feedback and information from others to evaluate their environment and peers. Through their interactions with others, individuals come to know better not only others but also themselves (Festinger 1954; Markus and Cross 1990). While this research does not rule out potential negative side effects of social interactions, it suggests that socialization greatly enhances the resources of individuals.

In this study, we adopt a more balanced view on the implications of social interactions for investor behavior and present theoretical analysis and empirical results from the housing market. The housing market could be a good testing ground to study social factors in financial decision-making for a variety of reasons. First, buying a home is one of the most important investment and consumption decisions most people make.[2] Second, home-buying transactions have been becoming increasingly complex over time. Third, the housing market could be also affected by status considerations, given that buying a home is a reliable signal which is easy to verify and costly to imitate (Hirsch 1976; Frank 2005). Finally, real estate markets have been vulnerable to overvaluations and crashes. For instance, the recent subprime mortgage crisis and the sharp rise in U.S. mortgage default rates over the 2007-2010-period led to the most severe financial crisis since the Great Depression (Mian and Sufi 2009, Khandani, Lo, and Merton 2012).

In the first part of the paper, we develop a stylized model of social contagion in real estate markets based on the work of Burnside, Eichenbaum, and Rebelo (2016) (henceforth, BER). The model considers an economy with three types of investors. *Sophisticated* investors have

[1]See e.g., Shiller (2015) and Pearson, Yang, and Zhang (2017). DeMarzo, Kaniel, and Kremer (2008) also show that social comparisons can lead to bubbles.

[2]According to the Bureau of Labor Statistics, housing expenditure accounted for 32.8 percent of household expenses for the average U.S. family in 2003 (http://www.bls.gov/opub/uscs/).

foresight about the long-term value of housing. *Optimistic* and *vulnerable* investors have sentiment-based beliefs that assign high and low values to housing, respectively. These investors interact with one another randomly and can influence each other's beliefs through their interaction. Sociability in the model is captured by the probability that any investor experiences an interaction. Investors with higher certainty in their beliefs can influence those with lower certainty, but not vice versa. As in the BER model, vulnerable investors are assumed to have beliefs with lowest certainty, so that they can be influenced by both sophisticates and optimists.[3] Sophisticates can influence optimists or vice versa, depending on which group has beliefs with stronger conviction.

A bubble in our model is defined as a condition in which prices become overvalued relative to fundamental value (i.e., the value assigned by rational investors). The likelihood for a bubble is determined by the proportion of optimists in the economy pushing demand up to irrationally exuberant levels. We show that higher sociability can increase the proportion of sophisticates and decrease the proportion of optimists if sophisticates exert high social influence, i.e., sophisticates have a high probability of convincing others of their view as a result of strong convictions or representation in the population. Thus, contrary to the prevailing intuition, social interactions could spread financial literacy throughout the population.

The model predicts that sociability can either fuel or suppress bubbles, depending on the relative influence of sophisticates versus optimists. When sophisticated investors dominate social interactions (in terms of conviction or numbers), sociability is negatively related to the likelihood of a bubble; when optimists dominate social interactions, sociability is positively related to likelihood of a bubble. This finding also stands in contrast to the aforementioned contagion propagation mechanism, in which higher sociability unambiguously increases the likelihood of bubbles (e.g., Shiller 2015).

In the second part of the paper, we present empirical evidence from the housing market. To address the implications of sociability for the housing market, we examine empirically local real estate markets across U.S. counties between 2003 and 2010. We measure county-level sociability with the social capital index developed at the NERCRD of Pennsylvania State University.[4] The index measures the civic engagement of local residents in a wide variety of activities ranging from civic, business, and social associations to public golf courses and sport clubs. We measure the house price-levels in a county with the House Price Index (HPI), developed by the Federal Housing Finance Agency (FHFA) and gather some basic demographic characteristics for each county from the 2006 American Community Survey personal-level data provided by the Integrated Public Use Microdata Series (IPUMS) database at the University of Minnesota (Ruggles et al., 2017).

[3] This assumption not only allows for the formation of bubbles, but is also consistent with empirical evidence on individual financial behavior (e.g., Puri and Robinson 2007).

[4] See the Northeast Regional Center for Rural Development (NERCRD) at: http://aese.psu.edu/nercrd.

In addition to the house price data, we also obtain basic mortgage loan data from the Loan Applications Registries (LARs) that were collected by the Federal Reserve under provisions of the Home Mortgage Disclosure Act (HMDA). A major advantage of the HMDA data is that it covers actual loan applications (including declined applications), which allows us to characterize well the local demand for housing in an area. We restrict our mortgage sample to the 2004-2006 period since it coincides with the climax of the real estate market in the recent subprime mortgage expansion. Our final sample covers 18.6 million applications over the 3-year sample period, approximately 15 million of which were accepted.

We find that county sociability is associated with larger number of loan applications. However, more sociable counties exhibit lower fraction of declined loan applications and subprime loans than less sociable counties. The effect is also economically significant. For example, a one standard deviation increase in county sociability results in 3 percent lower fraction of declined applications (for comparison, the standard deviation of the fraction of declined loan applications across counties is 9.8 percent). The results suggest that sociability promoted financial sophistication in the recent subprime mortgage expansion, which encouraged applications from higher credit borrowers and discouraged applications from lower credit borrowers.

Next, we study the relationship between sociability and bubble formation. Real estate prices escalated gradually over the 2003-2006 period, followed by a sharp rise in mortgage default rates that led to the most severe financial crisis since the Great Depression. Real estate market dynamics, however, exhibited dramatic differences across regions, which provides a unique opportunity to study the origin of bubbles and their relationship to local sociability. Consistent with the demand results, we find that more sociable counties were associated with smaller house price declines during the 2007-2010 period, indicating that bubble-formation correlates negatively with sociability.

Our model also predicts that the direction of the relationship between sociability and real estate bubbles depends on the number of sophisticated residents in the region. To address this contingency, we extend the baseline models by including two proxies for financial sophistication or local real estate expertise within the county: 1) the fraction of county population employed in banking and real estate and 2.) the number of mortgage originators in the county. We observe that both proxies of financial sophistication are positively correlated with bubbles. The interaction term of local sophistication and sociability, however, is negatively related to bubble-formation in the local real estate market. In other words, sociability reduces the likelihood for bubble-formation in areas with a larger number of sophisticated residents.[5] In sum, we present theoretical analysis and empirical evidence supporting the

[5]These findings suggest that although real estate and mortgage professionals helped fuel housing demand, they appear to have advised friends and associates in social settings more conservatively about prospects in local real estate markets. Other research corroborates the view that altruistic motives can improve the quality of advice provided by advisors and intermediaries (e.g., Gneezy 2005).

idea that sociability can significantly affect the demand and pricing in real estate markets and the effect of sociability depends crucially on the degree of financial sophistication in the area. When the number of sophisticated residents is relatively high, sociability promotes more conservative demand and more stable prices.

This paper contributes to the literature on social interactions and financial decision-making. Economists have established that social interaction could exhibit an important behavioral influence in settings such as retirement asset accumulation and decumulation (Banerjee and Park 2017, Favreau 2016, Duflo and Saez 2002 and 2003), lottery and stock market participation (Mitton, Vorkink, and Wright 2015, Brown, et al. 2008, and Hong, Kubik, and Stein 2004), stock trading (Ivković and Weisbenner 2007, Hong, Kubik, and Stein 2005, Kaustia and Knüpfer 2012, Ng and Wu 2010, Bursztyn, et al. 2014, Ouimet and Tate 2017), and home purchase and finance decisions (Maturana and Nickerson 2017, McCartney and Shah 2017, Gupta 2016, Bayer, Mangum, and Roberts 2016, Bailey, et al. 2017, and Guiso, Sapienza, and Zingales 2013). However, much of the literature tends to view social interactions as suboptimal.[6] Our results suggest that socialization could significantly improve financial decision making. Ambuehl, et al. (2017) reach a similar conclusion in an experimental setting. They show that communication between experimental subjects improves decision making in an investment task. Shive (2010) also finds evidence that socially transmitted trading information among Finnish households predicts stock returns, lending support to the idea that social interactions can transmit valuable information.

We also contribute to the literature on contagion and asset-pricing bubbles. Pearson, Yang, and Zhang (2017) find empirical evidence of social interactions contributing to the Chinese warrants bubble of 2007. Xiong and Yu (2011) provide compelling evidence that prices exceeded fundamental values during this episode. Levine, et al. (2014) find that ethnic homogeneity increases the likelihood of bubbles relative to ethnic diversity in an experimental setting. This outcome occurs presumably because homogeneity facilitates reliance on others' beliefs and the spread of mania. Our framework allows for sociability to increase the likelihood of a bubble if exuberant investors dominate social interactions. However, it also allows for sociability to suppress bubbles if sophisticates have sufficiently strong convictions or representation in the population.

We finally contribute to the literature on contagion in real estate markets. Bailey, et al. (2017) and Bayer, Mangum, and Roberts (2016) find that social media friends and neighbors, respectively, influence one another's home purchase decisions. However, neither

[6]Cao, Han, and Hirshleifer (2011) and Han, Hirshleifer, and Walden (2017) analyze models in which communication can lead to suboptimal outcomes. In the former model, imperfect communication (i.e., communication limited to decisions and outcomes) can lead to imperfect information aggregation and cascades. In the latter model, selective communication (omission) of trading gains (losses) can lead to the prevalence of high-cost active fund management. Massa and Simonov (2005) find that investor homogeneity reduces firm profitabitilty and returns while increasing volatility.

of these studies draws strong conclusions about the benefit or harm from such influence or its effect on house prices. In contrast, our study finds that social interaction has the potential to spread prudent home purchase and finance decisions and suppress bubbles in real estate markets.

The rest of the paper is organized as follows. Section II argues that social interaction in financial markets has the potential to be beneficial. Section III presents the model, while Section IV presents the empirical analysis. We conclude in Section V.

2 The Benefit of Social Interactions

Non-market interactions between people represent the majority of human experience. We are influenced by the actions of others; we also influence the people around us. Latane (1981) refers to these interpersonal effects as "social impact" and defines it as "the great variety of changes in physiological states and subjective feelings, motives and emotions, cognitions and beliefs, values and behavior, that occur in an individual, human or animal, as a result of the real, implied, or imagined presence or actions of other individuals."

There is extensive evidence in the literature that many economic actions, such as consumption, investment, crime, education choice, and labor force participation, are marked by social interactions (see e.g. Arndt, 1967, Akerlof, 1997, Becker, 1997, Bernheim, 1994, Young, 1997, Ellison et al.. 1995). However, the economics literature tends to view social interactions as a force pushing individuals away from optimal decision. In the informational cascades literature, individuals sub-optimally ignore their information and copy the behavior of others (Bikhchandani, et al. 1988 and Cao, Han, and Hirshleifer 2011). In the status literature, individuals would sub-optimally emulate the behavior of higher status groups in search of higher status (e.g. Glaeser, Sacerdote, Scheinkman 1996, Luttmer 2005, Duflo and Saez 2002, Frank 2005). Not surprisingly, most of the economic equilibria under social influence are characterized with excessive participation rates (Dupor and Liu 2003), abnormal risk-taking (Abel 1990, Chan and Kogan 2002, Roussanov 2010), and the formation of financial bubbles (DeMarzo, Kaniel, and Kremer 2007).

The views of economists on social interactions contrast strongly with the views of other social scientists. Many schools of thought currently accept the view that social interactions play a critical role in determining individual preferences, utility, and behavior (Bandura 1977, Wertsch 1991). People rely on the feedback and information from others to evaluate, maintain, and regulate their self-perception (Festinger 1954). Through their interactions with others, individuals come to know better not only others but also themselves (Markus and Cross 1990). In his path-breaking work, Gallup shows that the self-awareness in chimpanzees with prior social experience exceeded dramatically the self-awareness in chimpanzees raised in isolation (Gallup 1977). While these views do not rule out some negative externalities embedded in social interactions, they suggest that positive externalities exist and they are at least as strong as negative externalities.

There is also an evolutionary argument against the predominantly negative interpretation of social interactions. If social interactions were indeed predominantly suboptimal, one would expect that social norms would emerge in society to discourage social behavior. Yet, this is not the case. If anything, most social norms tend to encourage and facilitate cooperation and social interactions among individuals (Axelrod 1984).

In the context of financial decision making, social interactions have the potential to benefit consumers if they promote sophistication or literacy. There is extensive evidence in the literature that financial literacy is associated with both greater capital market participation and better financial decisions (e.g., Calvet, Campbell, and Sodini 2009). Rooij et al. (2011) also contend that lack of financial education could make people underestimate the benefits of long-term saving behavior, while Lusardi and Mitchell (2007) show that those who are not financially literate are less likely to plan for retirement and to accumulate wealth.

Two aforementioned studies find evidence that socially transmitted information can convey valuable information in an experimental setting with simulated consumer borrowing decisions (Ambuehl, et al. 2017) and in actual stock trading decisions among neighbors (Shive 2010). A number of studies also find that information can flow through social networks (e.g., college alumni/alumnae networks) from corporations to the benefit of mutual fund managers (Hong and Xu 2017 and Cohen, Frazzini, and Malloy 2008), banks (Engelberg, Gao, and Parsons 2012), and sell-side analysts (Cohen, Frazzini, and Malloy 2010).[7]

3 Model

Our model is essentially a three period version of the infinite horizon BER model. Our model differs in a few respects. First, it adds a parameter representing the sociability of investors in a particular housing market. In addition, the finite horizon in our model also allows us to derive prices analytically and make precise statements regarding the relationship between parameters such as sociability on the likelihood of a bubble. Finally, the BER model features agents that do not necessarily have any differential ability to forecast long-term home values. In contrast, our model features a class of sophisticated investors who have superior information about home values. Therefore, sociability has the potential to spread either financial sophistication or pure sentiment absent informational content.

[7] There is also literature which finds beneficial information flow through online social media to investors (see Chen, et al. 2014). Gray, Crawford, and Kern (2012) also find that hedge fund managers who share ideas with other managers online benefit in a number of ways. However, their findings do not necessarily imply a benefit to the fund managers who receive this information. We focus here on effects which propagate through more traditional forms of social interaction mediated by personal relationships.

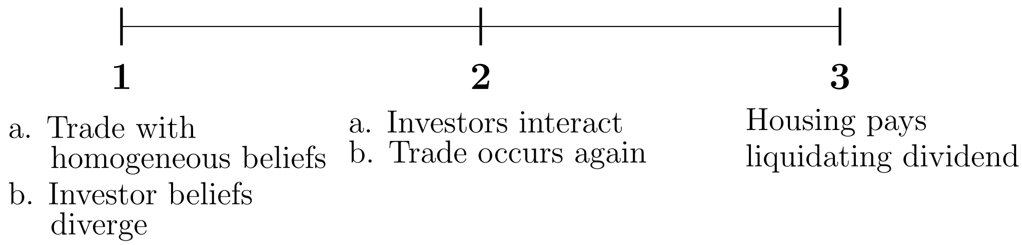

Figure 1: Model Timeline

Timing and Payoffs:

In our model, housing pays a stochastic liquidating dividend of $\widetilde{D}$, which reflects the future sale value of the home (in contrast to a stochastic utility stream derived from housing as in the BER model). We normalize both the consumption values of owning and renting to be zero for simplicity.[8] All agents start with homogeneous beliefs about the value of $\widetilde{D}$, agreeing about its expected value of $\bar{D}$. Trade then occurs at period 1. As in the BER model, a shock to sentiment follows this trade, which causes agents to shift their beliefs about $\widetilde{D}$ either upward or downward. In period 2, agents interact with one another and possibly influence each other's expectations in a way specified below. As in BER, our model focuses on social learning. In other words, agents only learn from social interaction with one another and not from observing trade, prices, or other opportunities for acquiring information. Trade then occurs again at the end of period 2. Housing pays its liquidating dividend at period 3. The timeline of the model is shown in figure 1.

Agents and Beliefs:

For simplicity, we assume that all agents are risk neutral and apply a zero discount rate to future payoffs. There is a continuum of agents with aggregate measure equal to one. There are three types of investors in the economy: optimistic, sophisticated, and vulnerable. At period 1, they have measures of o_1, s_1, and v_1 ($o_1 + s_1 + v_1 = 1$), respectively. After trade at period 1, optimistic investors adopt exuberant beliefs about home values. Their subjective expected value of $\widetilde{D}$ shifts upward to $D_H > \bar{D}$. Sophisticated investors have foresight about the long-term value of home prices.[9] They rationally revise their expected value for $\widetilde{D}$ up

[8]One could also interpret the liquidating dividend for housing to reflect current and future consumption values associated with home ownership.

[9]The BER model features *skeptical* agents, who believe home values to be low, in place of our sophisticated investors. As mentioned previously, neither skeptics nor optimists in their model necessarily have the ability to forecast long-term home prices. Our model focuses on the potential spread of financial sophistication versus the spread of mania through social interaction. Therefore, we include a class of sophisticated investors with greater foresight about long-term home values than others.

to D_H or down to $D_L < \bar{D}$ based on information. Vulnerable investors are pessimistic and shift their subjective value down to D_L.

As in the BER model, agents differ in the uncertainty of their beliefs about the value of $\widetilde{D}$, as measured by the entropy of their subjective distribution for this random variable.[10] The entropies of both optimistic investors (e^o) and sophisticated investors (e^s) are strictly less than that of vulnerable investors (e^v). Therefore, vulnerable investors are less certain in their beliefs than both optimists and sophisticates. We motivate this assumption in our discussion below.

Social Influence:

Each agent interacts with probability α with one other agent randomly selected from the population between trade at periods 1 and 2.[11] The parameter α is meant to capture the degree of sociability among investors as it reflects the probability of interactions. As in the BER model, agent i can only adopt the beliefs of agent j through this interaction if the entropy of agent i's belief is higher than that of agent j's (i.e., if agent j is more certain in her beliefs than agent i). The probability of "infection" between agent i and j (i.e., that i adopts the beliefs of j) is given by: $\gamma^{ji} = \max\{1 - e^j/e^i, 0\}$. Therefore, both optimistic and sophisticated investors can influence vulnerable investors (since both have beliefs with lower entropy than vulnerable investors). However, vulnerable investors can influence neither optimistic nor sophisticated investors. Optimists could influence sophisticates or vice versa, depending on which has beliefs with lower entropy.

We make the assumption that vulnerable investors have beliefs with the lowest certainty for a number of reasons. First, this assumption allows for the pool of optimists to grow over time, irrationally fueling housing demand and bubbles. The opposite assumption (i.e., the beliefs of optimists have lowest certainty) would allow for significant price descent followed by an upward "crash" in prices. There appears to be no empirical substantiation for such "negative" bubbles. In addition, optimistic individuals display behaviors consistent with overconfidence such as trading in individual equities (Puri and Robinson 2007).[12]

Prices:

As in the BER model, there is a fixed supply of housing for purchase of measure $k < 1$. Each agent can buy either one or zero units of housing. Therefore, only a measure k of agent can purchase homes in equilibrium, while the remaining agents rent. In equilibrium, there

[10]Entropy is defined formally to be the expectation of negative of the natural logarithm of the probability density function of a random variable.

[11]This infectious disease model was first developed by Bernoulli (1766) and applied to the real estate market by BER.

[12]Scheinkman and Xiong (2003) also develop a model in which certitude in beliefs (i.e., overconfidence) generates asset-pricing bubbles.

is a single price for housing which clears the market. Therefore, the equilibrium price for housing reflects the valuation of the marginal investor. In other words, it should be equal to the (1-k)'th percentile of reservation values for housing. All investors with reservation value above this price will buy housing, while all investors with reservation value below will rent.

Therefore, the equilibrium price for housing at period 1 is:

$$P_1 = \bar{D} \tag{1}$$

This value reflects the present value of the future dividend for all investors at period 1. The price of housing at period 2 is determined by the mass of investors who believe the expected value of $\widetilde{D}$ to be D_H. We refer to this mass as h which can take on two values:

$$h = \begin{cases} o_2 & \text{if} \quad E_2[\widetilde{D}] = D_L \\ o_2 + s_2 & \text{if} \quad E_2[\widetilde{D}] = D_H \end{cases} \tag{2}$$

where $E_2[\widetilde{D}]$ represents the rational (bayesian) expected home value at period 2. In the former case, only optimists believe $E[\widetilde{D}]$ to be D_H since the rational value is D_L. In the latter case, both optimists and sophisticates perceive $E_2[\widetilde{D}]$ to be equal to the rational expected value of D_H.

The price of housing at period 2 is equal to D_H (D_L) if h is greater (less) than k as the marginal buyer believes home values to be D_H (D_L). Consequently, the equilibrium price for housing at period 2 is given by:

$$P_2 = \begin{cases} D_H & \text{if} \quad h \geq k \\ D_L & \text{if} \quad h < k \end{cases} \tag{3}$$

We define a bubble episode as one with a period 2 price for housing of D_H and $E_2[\widetilde{D}] = D_L$ (i.e., housing prices exceed fundamental value). Our analysis below focuses on the relationship between sociability and the likelihood of bubbles. We consider the cases in which the entropy of the beliefs of optimists is higher than that of sophisticates and vice versa, separately.

Case One: $e^o < e^s$

In this case, optimists have greater certainty in their beliefs than sophisticates. Therefore, sophisticates become optimists if these two types of investors interact. At period 2, the mass of optimistic, sophisticated, and pessimistic investors are given by the following equations:

$$\begin{aligned} o_2 &= o_1 + \alpha(\gamma^{ov} o_1 v_1 + \gamma^{os} o_1 s_1) \\ s_2 &= s_1 + \alpha(\gamma^{sv} s_1 v_1 - \gamma^{os} o_1 s_1) \\ v_2 &= v_1 - \alpha(\gamma^{ov} o_1 v_1 + \gamma^{sv} s_1 v_1) \end{aligned} \tag{4}$$

The population of optimists increases between periods 1 and 2 as a result of social interaction because both vulnerable and sophisticated investors become optimists. In this case, sociability (as captured by α) increases the proportion of optimists at period 2. It also increases the likelihood of a bubble since the proportion of optimists determines prices as in equations 2 and 3 when homes have low fundamental value (i.e., $E_2[\widetilde{D}] = D_L$). This prediction is consistent with the aforementioned contagion mechanism for bubbles. Namely, social interaction spreads irrational beliefs about high future asset values. We can generate the opposite prediction when we consider the next case, in which sophisticates infect optimists when they interact.

Case Two: $e^s < e^o$

In this case, sophisticates have greater certainty in their beliefs than optimists. Therefore, optimists become sophisticates if these two types of investors interact. At period 2, the mass of optimistic, sophisticated, and pessimistic investors are given by the following equations:

$$\begin{aligned} o_2 &= o_1 + \alpha(\gamma^{ov} o_1 v_1 - \gamma^{so} o_1 s_1) \\ s_2 &= s_1 + \alpha(\gamma^{sv} s_1 v_1 + \gamma^{so} o_1 s_1) \\ v_2 &= v_1 - \alpha(\gamma^{ov} o_1 v_1 + \gamma^{sv} s_1 v_1) \end{aligned} \tag{5}$$

The population of sophisticates increases between periods 1 and 2 as a result of social interaction because both vulnerable and optimistic investors become sophisticates. The population of vulnerable investors decreases between periods 1 and 2 because they become either optimistic or sophisticated. In contrast, the population of optimists can either increase or decrease between periods 1 and 2 as a result of social interaction, depending on whether optimists are infecting vulnerable investors or sophisticates are infecting optimistic investors more rapidly. In the former case, sociability (as captured by α) increases the proportion of optimists at period 2. It also increases the likelihood of a bubble since the proportion of optimists determines prices when fundamental home values are low as before. In the latter case, sociability decreases the proportion of optimists and the likelihood of a bubble.

Formally, we have the following comparative statics if $e^s < e^o$:

1. The likelihood of a bubble is increasing in sociability (α) if $\gamma^{ov} v_1 > \gamma^{so} s_1$. It is decreasing in sociability if $\gamma^{ov} v_1 < \gamma^{so} s_1$.

2. The likelihood of a bubble is decreasing in the interaction of sociability (α) with the mass of sophisticates (s_1).

The first finding stands in contrast to the contagion bubbles mechanism and the view that communication among investors facilitates the spread of misinformation and mania in financial markets. Sociability can suppress bubbles if sophisticates: 1.) constitute a sufficiently large proportion of the population or 2.) have a sufficiently strong viewpoint so that the entropy of their beliefs is low (and γ^{so} is high). In this case, they exert strong social influence and can spread the word about overheated housing markets more rapidly than less sophisticated investors can spread mania.

As we discuss below, we find evidence of this relationship across regional housing markets in the US during the bubble period. Namely, sociability has a negative relationship with our measure of bubbles across regions. In addition, we find evidence of the second comparative static. In particular, this relationship is driven by the interaction of sociability with the proportion of agents who are particularly sophisticated with respect to the real estate market. These findings are consistent with our model when sophisticates have high social influence (i.e., they have a high probability of convincing others of their view as a result of strong convictions or representation in the population). We now turn our attention toward testing this theory using county-level data real estate data around the period of the US housing bubble.

4 Empirical Analysis

4.1 Sample

We compile our county-level database from multiple sources. We measure sociability in each county with the level of civic engagement of the residents in the county, provided by the Northeast Regional Center for Rural Development at the Pennsylvania State University. The civic engagement measure was developed by Rupasingha et al. (2006) and is constructed as the aggregate number of religious organizations, civic and social associations, business associations, political organizations, professional organizations, labor organizations, bowling centers, physical fitness facilities, public golf courses, and sport clubs in each county relative to total county population.

We measure the house price-levels in a county with the House Price Index (HPI), developed by the Federal Housing Finance Agency (FHFA).[13] The HPI for each geographic area is estimated using repeated observations of housing values for individual single-family residential properties on which at least two mortgages were originated and subsequently purchased by either Freddie Mac or Fannie Mae since 1975 (Calhoun 1996). The HPI index has been widely used as a broad measure of the movements of single-family house prices.

We gather some basic personal characteristics for each county from the 2006 American Community Survey personal-level data provided by the Integrated Public Use Microdata Series (IPUMS) database at the University of Minnesota (Ruggles et al., 2017). The smallest geographical area that the database identifies with respect to each person is the Public Use Microdata Area (PUMA), which generally follows the boundaries of a county. If the

[13]https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx

population of the county exceeds 200,000 residents, it is divided into as many PUMAs of 100,000+ residents as possible. In all these cases we "reverse-engineer" the county by aggregating the information from its corresponding PUMAs. Some small counties, on the other hand, are aggregated into one PUMA region, thus sharing the same census information. In all these cases, we assign to each county the corresponding PUMA-district variables.

We also obtain mortgage loan data from the Loan Applications Registries (LARs) that were collected by the Federal Reserve under provisions of the Home Mortgage Disclosure Act (HMDA). HMDA requires most mortgage lending institutions to disclose to the public information about the geographic location of their operations and some basic characteristics of the home loans they originate during a calendar year. We restrict our mortgage sample to the 2004-2006 period since it coincides with the climax of the real estate market. We stop at the end of 2006 because the subprime meltdown started by the second quarter of 2007.[14] Our final sample covers 18.6 million applications over the 3-year sample period, approximately 15 million of which were accepted.

Mortgage-originating institutions could be classified into three broad groups - banks, savings and loans (including credit unions), and lenders participating in the financing programs of US Department of Housing and Urban Development (HUD). Over the sample period, banks accounted for 56 percent of all originated loans, savings and loans for 16 percent, and HUD for 28 percent. HUD manages different programs that make housing more affordable and that protect customers from unfair lending. For example, they manage FHA loans that are issued for first-time- and moderate-income-home buyers and Section 8-renting for low-income and elderly-population. Throughout the paper, we have replicated all major tests by excluding HUD-institutions from the analysis and the results are qualitatively similar.

A major advantage of the HMDA data is that it covers actual loan applications (including declined applications), which could be informative about excess demand in a particular area. The data, however, provides very limited information on loan applicants. Given that numerous data-sources collect detailed regional demographic and socio-economic information, we organize our study at the county-level. This approach allows us to assess social influence-effects that survive aggregation and generate significant economic impact at the macro-level. Counties also exhibit substantial variation with respect to demographic characteristics, as well as subprime lending activity and house price appreciation rates.

4.2 Measuring Bubbles

Bubbles arise if the price of an asset exceeds its fundamental value. This can occur if investors hold the asset because they believe that they can sell it at an even higher price

[14] On April 2, 2007 New Century Financial, one of the nation's largest subprime mortgage lenders, filed for bankruptcy. Around the same time, Bear Stearns pledged up to $3.2 billion in loans to bail out two hedge funds hit by subprime losses and investor redemptions.

to some other investors later in the future. Brunnermeier (2007) defines bubbles as price paths of "dramatic asset price increases, followed by a collapse." His definition suggests two general approaches for the assessment of bubbles - an ex-ante approach, identifying abnormal expansion, and an ex-post approach, evaluating the contraction (collapse).

The ex-ante identification of bubbles requires a benchmark for 'fair pricing', which is a serious obstacle. As a result, we decide to focus on the ex-post identification. The US real estate market started contracting by the beginning of 2007, following a steady 5-year expansion. We measure real estate bubbles in a county with the average home-price decline in the county from 2007 till 2010. This approach for identifying bubbles is robust with respect to the actual asset pricing model in the market, given that the burst of the bubble represents an extreme exogenous shock to asset prices.

The five counties with the largest real estate bubbles over the sample period were Merced County, CA; Nye County, NV; Clark County, NV; Stanislaus County, CA; and St. Lucie, FL. In these counties real estate properties lost more than 50 percent of their values over the three year period from 2007 till 2010.

4.3 Results

Table 1 presents the distributional characteristics of all variables in the study. We observe that house prices experienced a significant 7.6 decline over the 2007-2010 period. However, there is a significant variation across counties - while the prices of real estate properties in some counties experienced a modest increase during the period, the real estate prices in a large group of counties dropped with close to 50 percent over the relatively short time-period. The table also reveals a significant variation in mortgage demand over the 2003-2006 period across counties. Around 23 percent of the mortgage applications in the average county were declined and around 14 percent of the originated loans during the period were subprime (with yields more the 300 basis points above the treasury rate). Counties also exhibited substantial variation with respect to the number of originators and fraction of real estate professionals. We use both of these variables as a measure of the degree of sophistication with respect to the real estate market in the county. Real estate and mortgage professionals are likely to possess substantial knowledge about the local real estate market, providing them with more accurate views about home values and stronger convictions about those views than non-professional homebuyers. For example, Kurlat and Stroebel (2015) show empirically that the number of real estate professionals in a neighborhood serves as a proxy for real estate expertise within a neighborhood. In addition, experimental research shows that professional experts can possess more accurate and stronger beliefs than non-professionals.[15] These real estate

[15]McKenzie, Liersch, and Yaniv (2008) have shown that professional experts can provide more accurate estimates and tighter confidence intervals than novices. Alevy, Haigh, and List (2007) also find that CBOT traders are less prone to herding and cascades than novice investors. Finally, Glaser, Weber, and Langer

and mortgage professionals are potential subjects for social interactions in the county as a result of residing in or around the area. Finally, Table 1 reveals that the average household income in a county was 52,000 USD, around 12.7 percent of the county population had a college degree, 50.9 percent were female, and 83.6 percent were white.

Table 2 reports cross-correlations of the sociability variable and county-level demographic characteristics. We observe that sociability does not exhibit any extreme collinearities with the regional characteristics, suggesting that the variable captures a novel element of the local culture. The data reveals that smaller counties with older and more educated population tend to be more social. Sociability also tends to correlate positively with the fraction of white population and negatively with the fraction of female population in the region.

Figure 1 plots the distribution of the sociability measure across all counties in US as of 2005. The figure shows that sociability exhibits a significant and non-trivial variation across regions. According to the measure, the most sociable states in US are DC, North Dakota, South Dakota, Nebraska, and Minnesota, while the least sociable states are Arizona, Georgia, Utah, California, and Tennessee.

Table 3 studies the link between county sociability and mortgage demand. We observe that counties with more sociable population experience larger number of loan applications. However, more sociable counties also have significantly less declined applications and accepted applications from low-credit borrowers with higher mortgage rates. These findings suggest that socialization propagates rational behavior. In particular, the results are consistent with our model when sophisticates have high social influence. In this case, sociability increases the proportion of sophisticates in the population. We expect fewer low-credit borrowers applying for mortgages when there is a greater proportion of sophisticates because sophisticated agents may disseminate information about credit risk in local markets or discourage residents with poor credit from applying. They may also encourage creditworthy borrowers to apply, consistent with the finding that sociability increases mortgage applications.

In Table 4, we link bubbles to sociability. The dependent variable is the drop in real estate prices during 2007-2010. We find that more social counties are associated with smaller real estate bubbles as measured by house price declines. Again, this finding is consistent with the model and suggests that sophisticated consumers exert high social influence in the average county. It stands in contrast to the implications of the contagion mechanism for bubbles, i.e., that social interaction unambiguously fuels mania by drawing in participation from new investors.

As discussed, our model also predicts that the interaction of sociability and the number of sophisticates is negatively related to the likelihood of bubbles if sophisticates exert high

(2008) also show that professional traders have more certitude in their estimates in a trend prediction task than non-professionals social influence. In other words, sociability can reduce the likelihood for bubble-formation in areas with a larger number of sophisticated residents. In the second and third models of the table, we interact sociability with the fraction of real estate and banking professionals or the number of mortgage originators in the county.

Our proxies for financial sophistication may also affect the supply of intermediation and financial services in the county. For example, the number of originators in an area may affect the supply of local credit. Consistent with this conjecture, we observe that the number of mortgage originators in a county is positively correlated with bubbles. The same is true for the fraction of real estate and banking professionals in the county. However, as mentioned previously, these variables are also related to the degree of financial sophistication in the county with respect to the real estate market. Real estate and mortgage professionals are likely to exert high influence in their social interactions with others as a result of the accuracy and conviction of their views. Consistent with the model, we observe that the interaction of either financial sophistication variable with the sociability variable is negatively related to the formation of bubbles. A high degree of opportunity for social interaction combined with a large proportion of sophisticated real estate or mortgage professionals decreases the likelihood of bubbles. Furthermore, the mediation effect of financial sophistication explains all of the negative effect of sociability on bubble-formation. We also observe that sociability exhibits a positive effect on bubble formation in counties with less sophisticated residents (as reflected in the main effect of the sociability variable) when measuring sophistication using mortgage originators. Sociability has no statistically significant effect after controlling for the interaction of sociability with the fraction of real estate and banking professionals. Therefore, sociability promotes more stable real estate prices only when the number of sophisticated residents in an area is sufficiently high.

These findings also indicate that real estate and mortgage professionals helped fuel housing demand by providing credit and intermediation services. However, these professionals appear to have advised friends and associates in social settings more conservatively about prospects in local real estate markets. This finding is consistent with the idea that the altruistic motives present in personal communications can improve the quality of advice provided by advisors and intermediaries (e.g., Gneezy 2005).

5 Conclusion

Did social interactions fuel or suppress the US housing bubble? The default response to this question by many economists would have been the former. Currently, most theoretical frameworks in economics and finance tend to see social interactions as a suboptimal and destabilizing force pushing demands and prices beyond desirable levels. In this paper, we challenge this understanding.

We present a theoretical model of financial markets in which investors exhibit different degrees of sophistication and can influence each other's beliefs through their interaction. The model predicts that sociability can either fuel or suppress bubbles, depending on the relative influence of more sophisticated versus less sophisticated investors. When sophisticated investors dominate social interactions, sociability is negatively related to the likelihood of a bubble; when sentiment-driven optimists dominate social interactions, sociability is positively related to likelihood of a bubble. We also present empirical evidence consistent with the theoretical framework from the recent housing bubble. We find that only when the number of sophisticated residents in an area is sufficiently high does sociability promote more stable real estate prices.

At least one experimental by Ambuehl, et al. (2017) corroborates our finding that social interactions can spread financial sophistication between individuals. Further research can address the question of whether such effects might exist in other financial market settings.

Appendix A: Variables Description

Variable	Description and Data-sources
Sociability	A measure of the level of civic engagement of the residents in a county, constructed as the aggregate number of religious organizations, civic and social associations, business associations, political organizations, professional organizations, labor organizations, bowling centers, physical fitness facilities, public golf courses, and sport clubs in each county relative to total county population. *Source*: Rupasingha et al. (2006)
Price Drop in 2007-2010	The percentage house price decline in a county from 2007 to 2010 based on the county-level House Price Index (HPI) developed by FHFA. *Source*: Federal Housing Finance Agency
Num. mortgage applications	The average annual total number of home-purchase mortgage applications in a county over 2004-2006. *Source*: HMDA
% Declined Applications	The average fraction of declined home-purchase mortgage applications in a county relative to the total number of applications over 2004-2006. *Source*: HMDA
% Subprime Loans	The average fraction of subprime home-purchase loans originated in a county relative to the total number of loans over 2004-2006. Subprime loans are identified by a flag for loans with APRs that are 3 percentage points above a comparable Treasury APR. *Source*: HMDA
Average spread	The average yield spread on all single-home mortgage loans in a county relative to comparable Treasury APR. The yield spread on all prime loans (with yield spread less than 3 percent) is assumed to be 1.5 percent since it is not reported. *Source*: HMDA
Num. Originators	The average number of mortgage originating institutions in a county over 2004-2006. *Source*: HMDA
Frac. in Real Estate	The fraction of county population employed in banking and real estate. *Source*: 2006 American Community Survey (ACS)
County population	Total county population. *Source*: 2006 ACS
Home ownership	The home ownership rate in a county. *Source*: 2006 ACS
Income	The average income in a county. *Source*: 2006 ACS
Age	The average age of all residents in a county. *Source*: 2006 ACS
Education	The fraction of residents with a college degree in a county. *Source*: 2006 ACS
Female	The fraction of female residents in a county. *Source*: 2006 ACS
White	The fraction of white residents in a county. *Source*: 2006 ACS

References

Akerlof, George. 1997. Social Distance and Social Decisions. *Econometrica* 65: 1005-1027.

Alevy, Jonathan E., Michael S. Haigh, and John A. List. 2007. Information Cascades: Evidence from a Field Experiment with Financial Market Professionals. *The Journal of Finance* 62(1): 151-180/.

Ambuehl, Sandro, B. Douglas Bernheim, Fulya Ersoy, and Donhatal Harris. 2017. Social Transmission of Financial Decision Making Skills: A Case of the Blind Leading the Blind? *Rotman School of Management Working Paper No. 2891753*.

Arndt, Johan. 1967. Role of Product-Related Conversations in the Diffusion of a New Product. *Journal of Marketing Research* 4: 291–95.

Axelrod, R. 1984: The Evolution of Co-operation, New York: Basic Books

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel. 2017. The Economic Effects of Social Networks: Evidence from Housing Market. *Journal of Political Economy* Forthcoming.

Bandura, A. Social Learning Theory. Oxford, England: Prentice-Hall (1977).

Banerjee, Abhijit. 1992. A Simple Model of Herd Behavior. *Quarterly Journal of Economics* 107: 797-817.

Banerjee, Abhijit, and Drew Fudenberg. 2004. Word-of-Mouth Learning. *Games and Economic Behavior* 46: 1-22.

Banerjee, Sudipto and Youngkyun Park. 2017. Social Interaction at Workplace and the Decision to Annuitize Pension Assets. *Working Paper.*

Barsky, Robert, Thomas Juster, Miles Kimball, and Matthew Shapiro. 1997. Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study. *Quarterly Journal of Economics* 112: 537–579.

Bayer, Patrick, Kyle Mangum, and James Roberts. 2016. Speculative Fever: Investor Contagion in the Housing Bubble. *NBER Working Paper No*. 22065.

Bertrand, Marianne, Erzo Luttmer, and Sendhil Mullainathan. 2000. Network Effects and Welfare Cultures. *Quarterly Journal of Economics* 115: 1019-1057.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1998. Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades. *Journal of Economic Perspectives* 12: 151-170.

Black, Harold, Robert L. Schweitzer, and Lewis Mandell. 1978. .Discrimination in Mortgage Lending. *American Economic Review* 68: 186-191.

Bond, Philip, Dvid K. Musto and Bilge Yilmaz. 2009. Predatory Mortgage Lending. *Journal of Financial Economics* 94: 412-427.

Borjas, George. 1995. Ethnicity, Neighborhoods, and Human-Capital Externalities. *American Economic Review* 85: 365-390.

Brown, Jacqueline Johnson and Peter H. Reingen. 1987. Social Ties and Word-of-Mouth Referral Behavior. *Journal of Consumer Research* 14: 350–62.

Brown. Jeffrey R., Zoran Ivković, Paul A. Smith, and Scott Weisbenner. 2008. Neighbors Matter: Causal Community Effects and Stock Market Participation. *The Journal of Finance* 63(3): 1509-1531.

Brunnermeier, Markus, and Christian Julliard. 2008. Money Illusion and Housing Frenzies. *Review of Financial Studies* 21: 135-180.

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo. 2016. Understanding Booms and Busts in Housing Markets. *Journal of Political Economy* 124(4): 1088-1147.

Bursztyn. Leonardo, Florian Ederer, Bruno Ferman, and Noam Yachtman. 2014. Understanding Mechanisms Underlying Peer Effects:Evidence from a Field Experiment on Financial Decisions. *Econometrica* 82(4): 1273-1301.

Calhoun, C. 1996. OFHEO House Price Indexes: HPI Technical Description, official OFHEO document.

Calvet, L.; J. Campbell; and P. Sodini. "Measuring the Financial Sophistication of Households." American Economic Review, 99 (2009), 393–398.

Campbell, John. 2006. Household Finance. *Journal of Finance* 61: 1553-1604.

Carlin, Bruce. 2009. Strategic Price Complexity in Retail Financial Markts. *Journal of Financial Economics* 91: 278-287.

Cao, H. Henry, Bing Han, and David Hirshleifer. 2011. Taking the Road Less Traveled By: Does Coversation Eradicate Pernicious Cascades? *Journal of Economic Theory* 146: 1418-1436.

Celen, Bogachan, Shachar Kariv, and Andrew Schotter. 2010. An Experimental Test of Advice and Social Learning. *Management Science* 56: 1687-1701.

Chan, Yeung Lewis, and Leonid Kogan. 2002. Catching Up with the Joneses: Heterogeneous Preferences and the Dynamics of Asset Prices. *Journal of Political Economy* 110: 1255-1285.

Chen, Hailiang, Prabuddha De., Yu (Jeffrey) Hu, and Byoung-Hyoun Hwang. 2014. Wisdom of Crowds: The Value of Stock Opinions Transmitted through Social Media. *Review of Financial Studies* 27(5): 1367-1403.

Cohen, Lauren, Andrea Frazzini, and Christopher J. Malloy. 2008. The Small World of Investing: Board Connections and Mutual Fund Returns. *Journal of Political Economy* 11: 951–979.

Cohen, Lauren, Andrea Frazzini, and Christopher J. Malloy. 2010. Sell-side School Ties. *Journal of Finance* 65(4): 1409-1437.

Cronqvist, Henrik, Florian Münkel, and Stephan Siegel. 2012. Genetics, Homeownership, and Home Location Choice. *Journal of Real Estate Finance and Economics* May: 1-33.

Dana, Jason and George Loewenstein. 2003. A Social Science Perspective on Gifts to Physicians from Industry. *Journal of the American Medical Association* 9(2): 252-255.

DeMarzo, Peter, Ron Kaniel, and Ilan Kremer. 2008. Relative Wealth Concerns and Financial Bubbles. *Review of Financial Studies* 21: 19–50.

Dhar, Ravi, and Ning Zhu. 2006. Up, Close and Personal: An Individual Level Analysis of the Disposition Effect. *Management Science* 52: 726–740.

Duflo, Esther, and Emmanuel Saez. 2002. Participation and Investment Decisions in a Retirement Plan: The Influence of Colleagues' Choices. *Journal of Public Economics* 85: 121–148.

Duflo, Esther, and Emmanuel Saez. 2003. The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *Quarterly Journal of Economics* 118 (3), 815-842.

Dupor, Bill, and Wen-Fang Liu. 2003. Jealousy and Equilibrium Overconsumption. *American Economic Review* 93: 423–428.

Ellison, Glenn, and Drew Fudenberg. 1995. Word-of-Mouth Communication and Social Learning. *Quarterly Journal of Economics* 110: 93-125.

Engelberg, Joseph, Pengjie Gao, and Christopher A. Parsons, 2012, Friends with Money. *Journal of Financial Economics* 103, 169–188.

Epple, Dennis, and Glenn Platt. 1998. Equilibrium and Local Redistribution in an Urban Economy when Households Differ in Both Preferences and Income. *Journal of Urban Economics* 43: 23-51.

Epple, Dennis, and Holger Sieg. 1999. Estimating Equilibrium Models of Local Jurisdictions. *Journal of Political Economy* 107: 645-681.

Evans, William N., Wallace Oates, and Robert M. Schwab. 1992. Measuring Peer Group Effects: A Model of Teenage Behavior. *Journal of Political Economy* 100: 966-991.

Favreau, Charles. 2016. Does Social Conformity Influence Portfolio Choice? Evidence from 401(k) Allocations. *Duquesne University Working Paper.*

Festinger, L. A Theory of Social Comparison Processes. Human Relations 7, 117–140 (1954).

Frank, Robert. 2005. Positional Externalities Cause Large and Preventable Welfare Losses. *American Economic Review Papers and Proceedings* 45: 137–141.

Gallup, G. G. Self-recognition in primates: A comparative approach to the bidirectional properties of consciousness. American Psychologist 32, 329–338 (1977).

Glaeser, Edward, Bruce Sacerdote, and Jose Scheinkman. 1996. Crime and Social Interactions. *Quarterly Journal of Economics* 112: 507-48.

Gneezy, Uri. 2005. Deception: The Role of Consequences. *The American Economic Review* 95(1) 384-394.

Gray, Wesley R., Steve Crawford, and Andrew E. Kern. 2012. Do Hedge Fund Managers Identify and Share Profitable Ideas? *Drexel University Working Paper.*

Grier, Sonya A., and Rohit Deshpandé. 2001. .Social Dimensions of Consumer Distinctiveness: The Influence of Social Status on Group Identity and Adve8rtising Persuasion. *Journal of Marketing Research* 38: 216-224.

Grinblatt, Mark, Matti Keloharju, and Seppo Ikäheimo. 2008. Social Influence and Consumption: Evidence from the Automobile Purchases of Neighbors. *Review of Economics and Statistics* 90: 735-753.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales. 2013. The Determinants of Attitudes toward Strategic Default on Mortgages. *The Journal of Finance* 68(4) 1473-1515.

Gupta, Arpit. 2016. Foreclosure Contagion and the Neighborhood Spillover Effects of Mortgage Defaults. *NYU Working Paper*.

Halek, Martin, and Joseph Eisenhauer. 2001. Demography of Risk Aversion. *Journal of Risk and Insurance* 68: 1-24.

Han, Bing, David Hirshleifer, and Johan Walden. 2017. Social Transmission Bias and Investor Behavior. *Working Paper*.

Herr, Paul M., Frank R. Kardes, and John Kim. 1991. Effects of Word-of-Mouth and Product Attribute Information on Persuasion: An Accessibility-Diagnosticity Perspective. *Journal of Consumer Research* 17: 454-462.

Hilary, Gilles, and Kai Wai Hui. 2009. Does Religion Matter in Corporate Decision Making in America? *Journal of Financial Economics* 93: 455-473.

Hirsch, Fred. 1976. *The Social Limits to Growth*. London: Routledge & Kegan Paul.

Hofstede, Geert. 1980. *Culture's Consequences: International Differences in Work-related Values*. Beverly Hills, CA: Sage.

Hogg, Michael, and Dominic Abrams. 1988. *Social Identification: A Social Psychology of Intergroup Relations and Group Processes*. London: Routledge.

Hong, Harrison, Kubik, Jeffrey D., and Jeremy C. Stein. 2004. Social Interaction and Stock Market Participation. *Journal of Finance* 59: 137-163.

Hong, Harrison, Kubik, Jeffrey D., and Jeremy C. Stein. 2005. Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers. *Journal of Finance* 60(6): 2801-2824.

Hong, Harrison and Jiangmin Xu. 2017. Inferring Latent Networks from Stock Holdings. *Journal of Financial Economics* Forthcoming.

Ivković, Zoran and Scott Weisbenner. 2007. Information Diffusion Effects in Individual Investors' Common Stock Purchases: Covet Thy Neighbors' Investment Choices. *The Review of Financial Studies* 20(4): 1327-1357.

Jaffee, Dwight. 2008 The U.S. Subprime Mortgage Crisis: Issues Raised and Lessons Learned. Commission on Growth and Development and the World Bank, *Working Paper* No. 28.

Kaustia, Markku and Samuli Knüpfer. 2012. *Journal of Financial Economics* 104: 321-338.

Keys, Benjamin, Tanmoy Mukherjee, Amit Seru, and Vikrant Vig. 2010. Did Securitization Lead to Lax Screening? Evidence from Subprime Loans. *Quarterly Journal of Economics* 125: 307-362.

Khandani, Amir, Andrew Lo, and Robert Merton. 2012. Systemic Risk and the Refinancing Ratchet Effect. MIT Sloan Research Paper No. 4750-09; Harvard Business School Finance Working Paper No. 1472892.

Kling, Jeffrey R., Jens Ludwig, and Lawrence F. Katz. 2005. Neighborhood Effects on Crime for Female and Male Youth: Evidence from a Randomized Housing Mobility Experiment. *Quarterly Journal of Economics* 120: 87-130.

Kurlat, Pablo and Johannes Stroebel. 2015. Testing for Information Asymmetries in Real Estate Markets. *The Review of Financial Studies* 28(8): 2429-2461.

Laczniak, Russell N., Thomas E. DeCarlo, and Sridhar N.Ramaswami. 2001. Consumers' Responses to Negative Word of Mouth Communication: An Attribution Theory Perspective. *Journal of Consumer Psychology* 11: 57–73.

Latan´e B. 1981. The psychology of social impact. *American Psychologist* 36, 343–56

Lazear, Edward. 1999. Culture and Language. *Quarterly Journal of Economics* 107: S95–S126.

Levine, Sheen S., Evan P. Apfelbaum, Mark Bernard, Valerie L. Bartelt, Edward J. Zajac, and David Stark. 2014. Ethnic Diversity Deflates Price Bubbles. *PNAS* 111(52): 18524-18529.

List, John. 2003. Does Market Experience Eliminate Market Anomalies? *Quarterly Journal of Economics* 118: 41–71.

Lusardi, Annamaria, and Olivia Mitchell. 2007. Financial Literacy and Retirement Preparedness: Evidence and Implications for Financial Education Programs. Michigan Retirement Research Center Research Paper No. WP 2006-144.

Lusardi, A., and O. S. Mitchell. "Baby Boomers Retirement Security: The Role of Planning, Financial Literacy and Housing Wealth." Journal of Monetary Economics, 54 (2007), 205–224.

Lusardi, Annamaria, and Peter Tufano. 2009. Debt Literacy, Financial Experiences, and Overindebtedness. NBER Working Paper No. 14808.

Luttmer, Erzo F. P. 2005. "Neighbors as Negatives: Relative Earnings and Well- Being." Quarterly Journal of Economics 120, no. 3: 963–1002.

Madrian, Brigitte, and Dennis Shea. 2001. The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior. *Quarterly Journal of Economics* 116: 1149–1187.

Manski, Charles. 1993. Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies* 60: 531-542.

Manski, Charles. 2000. Economic Analysis of Social Interactions. *Journal of Economic Perspectives* 14: 115-136.

Massa, Massimo and Andrei Simonov. 2005. History Versus Geography: The Role of College Interaction in Portfolio Choice. *INSEAD working paper.*

Maturana, Gonzalo and Jordan Nickerson. 2017. Teachers Teaching Teachers: The Role of Networks on Financial Decisions, *Working Paper.*

Markus, H., & Cross, S. The interpersonal self. In L. A. Pervin (Ed.), Handbook of personality: Theory and research (pp. 576–608). New York: Guilford (1990).

McCartney, Benedict and Avni Shah. 2017. 'I'll Have What She's Having': Identifying Social Influence in Household Mortgage Decisions. *Working Paper.*

Mian, Atif, and Amir Sufi. 2009. The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis. *Quarterly Journal of Economics* 124: 1449–1496.

Mian, Atif, Amir Sufi, and Francesco Trebbi. 2010. The Political Economy of the U.S. Mortgage Default Crisis. *American Economic Review* 100: 1967-1998.

Mitton, Todd, Keith Vorkink, and Ian Wright. 2015. Neighborhood Effects on Speculative Behavior. *BYU Working Paper.*

Montgomery, D.C. 2005, *Design and Analysis of Experiments*, sixth ed., John Wiley & Sons.

Munnell, Alicia, Geoffrey Tootell, Lynn Browne, and James McEneaney. 1996. Mortgage Lending in Boston: Interpreting HMDA Data. *American Economic Review* 86: 25-53.

Ng, Lilian and Fei Wu. 2010. Peer Effects in the Trading Decisions of Individual Investors. *Financial Management* 807-831.

Ouimet, Paige and Geoffrey Tate. 2017. Learning from Coworkers: Peer Effects on Individual Investment Decisions. *UNC Chapel Hill Working Paper.*

Pearson, Neil D., Zhishu Yang, and Qi Zhang. 2017. Evidence about Bubble Mechanisms: Precipitating Event, Feedback Trading, and Social Contagion. *Working Paper.*

Puri, Manju and David T. Robinson. 2007. Optimism and Economic Choice. *Journal of Financial Economics* 86: 71-99.

Rooij, M.; A. Lusardi; and R. Alessie. 2011. Financial Literacy and Stock Market Participation. *Journal of Financial Economics* 101: 449-472.

Roussanov, Nikolai. 2010. Diversification and Its Discontents: Idiosyncratic and Entrepreneurial Risk in the Quest for Social Status. *Journal of Finance* 65: 1755–1788.

Steven Ruggles, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. Integrated Public Use Microdata Series: *Version 7.0.* Minneapolis: University of Minnesota, 2017.

Rupasingha, A., Goetz, S. J., & Freshwater, D. (2006). The production of social capital in US counties. Journal of Socio-Economics, 35, 83–101. doi:10.1016/j.socec.2005.11.001.

Sacerdote, Bruce. 2001. Peer Effects with Random Assignment: Results for Dartmouth Roommates. *Quarterly Journal of Economics* 116: 681-704.

Schwartz, Shalom. 1994. *Beyond Individualism/Collectivism: New Cultural Dimensions of Values*. In U. Kim, H. C. Triandis, C. Kagitcibasi, S. C. Choi, & G. Yoon (Eds.), Individualism and collectivism: Theory, methods, and applications (pp. 85–119). Thousand Oaks: Sage Publications.

Scheinkman, Jose and Wei Xiong. 2003. Overconfidence and Speculative Bubbles. Journal of the Political Economy 111 (6): 1183-1219.

Shiller, Robert. 2015. *Irrational Exuberance (3rd ed.)*. Princeton University Press, Princeton, NJ.

Shive, Sophie. 2010. An Epidemic Model of Investor Behavior. *The Journal of Financial and Quantitative Analysis* 45(1): 169-198..

Smith, Adam. 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations*, Volumes I and II. R. H. Campbell and A. S. Skinner, eds. Liberty Fund: Indianapolis.

Stulz, René, and Rohan Williamson. 2003. Culture, Openness, and Finance. *Journal of Financial Economics* 70: 313-349.

Tiebout, Charles. 1956. A Pure Theory of Local Expenditures. *Journal of Political Economy* 64: 416-424.

Topa, Giorgio. 2001. Social Interactions, Local Spillovers, and Unemployment. *Review of Economic Studies* 68: 261-295.

Veblen, Thorstein. 1899. *The Theory of the Leisure Class: An Economic Study of Institutions*. New York: Penguin.

Weber, Max. 1958. *The Protestant Ethic and the Spirit Of Capitalism*. Translated by Talcott Parsons. Allen & Unwin, London, U.K.

Weinberg, Bruce, Patricia Reagan, and Jeffrey Yankow. 2004. Do Neighborhoods Affect Hours Worked? Evidence from Longitudinal Data. *Journal of Labor Economics* 22: 891-924.

Wertsch, J. V. Voices of the mind: A sociocultural approach to mediated action. Cambridge, MA: Harvard University Press (1991).

Xiong, Wei and Jialan Yu. 2011. The Chinese Warrants Bubble. *American Economic Review* 101: 2723-2753.

Yancey, William L., Eugene P. Ericksen, and Richard N. Juliani. 1976. Emergent Ethnicity: A Review and Reformulation. *American Sociological Review* 41: 391-403.

Table 1 – Sample characteristics

Here we report distributional characteristics of the main variables in the analysis – sociability, a measure of the level of civic engagement of the residents in a county; Drop in 2007-2010, the percentage house price decline in a county from 2007 to 2010; Num. mortgage applications, the total number of home-purchase mortgage applications in a county; % Declined Applications, the fraction of declined home-purchase mortgage applications in a county relative to the total number of applications; % Subprime Loans, the fraction of subprime home-purchase loans originated in a county relative to the total number of loans; Average spread, the average yield spread on all single-home mortgage loans in a county relative to comparable Treasury APR; Num. Originators, the number of mortgage originating institutions in a county; Fraction in Real Estate, the fraction of county population employed in banking and real estate; county population; homeownership rate; average income; average age; and the fraction of educated, female, and white residents in the county.

	Mean	Standard Deviation	P1	Median	P99
Sociability	0.000	1.393	–2.577	–0.232	4.071
Drop in 2007-2010	0.076	0.103	–0.094	0.054	0.432
Num. mortgage applications (log)	5.986	1.870	1.674	5.910	10.298
% Declined Applications	0.233	0.098	0.082	0.212	0.541
% Subprime Loans	0.144	0.059	0.049	0.132	0.350
Average spread (log)	1.614	0.076	1.368	1.624	1.768
Num. Originators (log)	3.621	1.178	0.405	3.784	5.729
Fraction in Real Estate	0.023	0.009	0.009	0.022	0.054
County population (mil.)	0.065	0.205	0.001	0.017	0.815
Home ownership	0.781	0.065	0.568	0.790	0.902
Income (mil.)	0.061	0.014	0.043	0.058	0.113
Age	49.907	2.346	43.793	50.143	54.588
Education	0.193	0.074	0.100	0.173	0.456
Female	0.517	0.021	0.453	0.518	0.567
White	0.864	0.139	0.428	0.925	0.990

Table 2 – Correlations of Sociability and Local Demographic Characteristics

The table reports correlations of the following county-level variables – sociability, a measure of the level of civic engagement of the residents in a county; county population; county average income; county average age; and the fraction of educated, female, and white residents in the county. (*) indicate statistical significance at the 0.10 level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Sociability	1	–0.13*	0.05*	0.31*	0.12*	–0.13*	0.39*
2. Population		1	0.38*	–0.25*	0.35*	0.11*	–0.18*
3. Income			1	–0.39*	0.83*	–0.06*	0.02
4. Age				1	–0.37*	0.04*	0.35*
5. Education					1	0.03	0.01
6. Female						1	–0.17*
7. White							1

Table 3 – Sociability and Mortgage Demand

The table reports the coefficient estimates and P-values from OLS regressions of the number of loan applications; the fraction of declined loan applications; the fraction of subprime loans; and the average loan spread in a county over the 2004-2006 period on county sociability, (log of) the number of mortgage originating institutions in the county; county population; homeownership rate; average income; average age; and fraction of educated, female, and white residents in the county. Detailed definitions of all variables are provided in the Appendix. All models include state fixed effects and P-values are adjusted for clustering at the state-level. The last two rows report the number of observations and R-squares in each regression. (***), (**), and (*) indicate statistical significance at the 0.001, 0.05 and 0.10 level, respectively.

	# Loan Applications	% Declined Applications	% Subprime Loans	Average Spread
SOCL	0.035***	–0.022***	–0.009***	–0.008***
	0.0068	<.0001	<.0001	0.0096
Num. Originators	1.394***	–0.052***	–0.020***	0.014***
	<.0001	<.0001	<.0001	0.0002
County population	0.979***	0.041***	0.019***	–0.002
	0.0019	0.0039	0.0071	0.7039
Home ownership	–0.452*	0.080	0.028	0.121***
	0.0727	0.1099	0.2727	0.0004
Average income	2.964	–0.765*	–0.156	0.254
	0.2062	0.0761	0.3819	0.3446
Age	–0.030***	0.002**	0.000	–0.004***
	0.0012	0.0376	0.8637	<.0001
Education	1.293***	–0.058	–0.145***	0.012
	<.0001	0.275	<.0001	0.7873
Female	3.529***	0.238**	0.154**	0.083
	0.0006	0.0459	0.0273	0.414
White	0.035	–0.163***	–0.068***	–0.070***
	0.8614	<.0001	<.0001	0.0002
Intercept	0.515	0.306***	0.194***	1.718***
	0.5589	0.0005	<.0001	<.0001
Num. Observations	3,062	3,062	3,062	3,059
Adj. R– square	96.00	58.39	50.33	26.44

Table 4 – Sociability and Real estate Prices during 2003–2010

The table reports the coefficient estimates and P-values from OLS regressions of the percentage house price decline in a county from 2007 to 2010 on county sociability (SOCL), the financial sophistication of the population in the county (FIN.SOPH (K)); an interaction term of the sociability variable and the sophistication variable, county population; county homeownership rate; county average income; average age; and fraction of educated, female, and white residents in the county. The second model proxies financial sophistication with the (log of) the number of mortgage originating institutions in a county (K=1), while the third model proxies financial sophistication with the fraction of county population employed in banking and real estate (K=2). Detailed definitions of all variables are provided in the Appendix. All models include state fixed effects and P-values are adjusted for clustering at the state-level. The last two rows report the number of observations and R-squares in each regression. (***), (**), and (*) indicate statistical significance at the 0.001, 0.05 and 0.10 level, respectively.

		K = 1	K = 2
SOCL	–0.014***	0.032**	0.000
	0.0002	0.0133	0.9518
FIN.SOPH (K)		0.037***	1.363***
		<.0001	<.0001
SOCL* FIN.SOPH (K)		–0.011***	–0.599***
		0.0022	0.0037
County population	0.019	–0.020*	0.006
	0.2941	0.0651	0.7163
Home ownership	0.000	–0.021	–0.005
	0.9969	0.6005	0.879
Average income	2.693***	2.010***	2.225***
	<.0001	<.0001	<.0001
Age	0.001	0.004**	0.001
	0.6389	0.0129	0.5385
Education	–0.226***	–0.222***	–0.248***
	0.0034	0.0007	0.0005
Female	0.108	–0.160**	0.061
	0.2424	0.0364	0.4793
White	0.023	0.008	0.014
	0.1967	0.6233	0.3833
Intercept	–0.206**	–0.300***	–0.175*
	0.0375	0.0005	0.053
Num. Observations	2,372	2,372	2,372
Adj. R– square	69.19	72.72	70.32

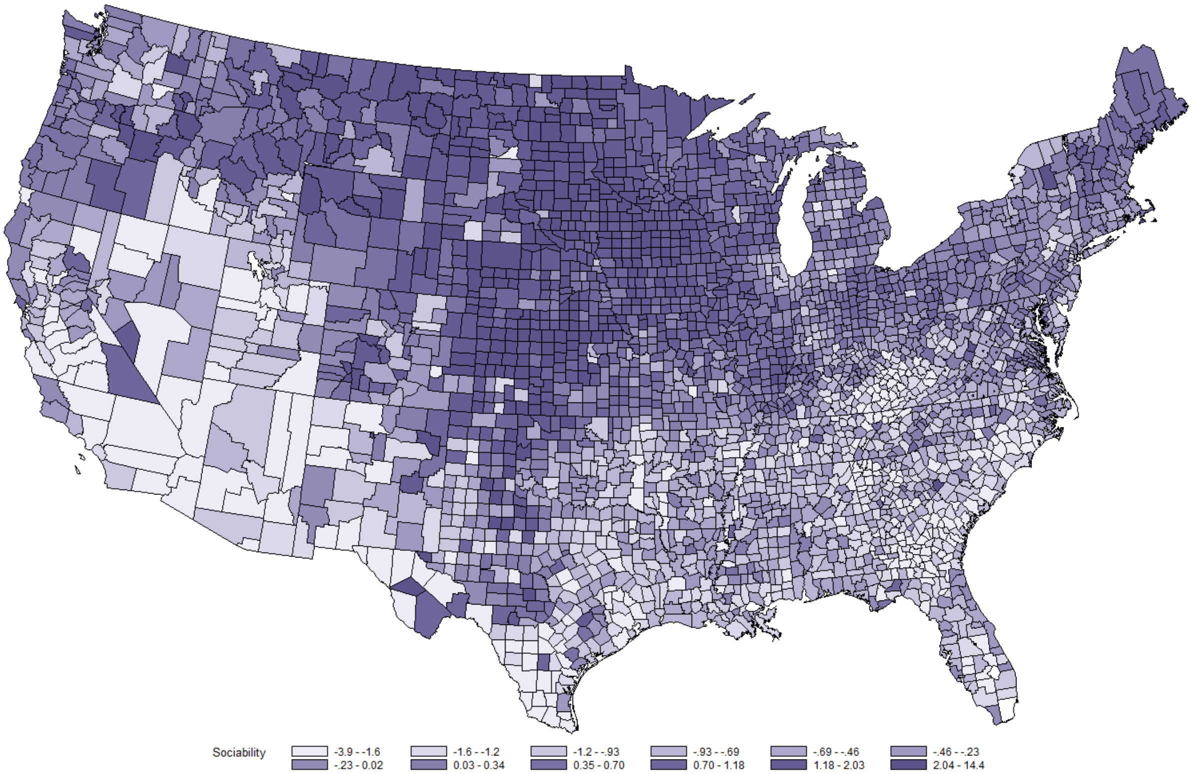

Figure 1. Geographic Distribution of Sociability
The figure presents the distribution of the sociability measure across all counties in US as of 2005.