Strategic Mortgage Default 
in the Context of a Social Network

by

Michael J. Seiler*
Professor and Robert M. Stanton Chair of Real Estate and Economic Development
Founder and Director, Institute for Behavioral and Experimental Real Estate (IBERE)
Old Dominion University
2154 Constant Hall
Norfolk, VA 23529-0223
mseiler@odu.edu
757.683.3505 phone
757.683.3258 fax

Andrew J. Collins
Virginia Modeling, Analysis, and Simulation Center (VMASC)
Old Dominion University
Norfolk, VA 23529
ajcollin@odu.edu

and

Nina H. Fefferman
Department of Ecology, Evolution, and Natural Resources
Rutgers University
Cook Campus; ENR building #134
14 College Farm Road
New Brunswick, NJ, 08901
fefferman@aesop.rutgers.edu

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* Contact author
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Abstract

A serious and imminent threat to a recovery of the global recession comes in the form of a burgeoning financial contagion known as strategic mortgage default. We theorize that the advocacy of strategic default can be likened to a disease, and as such, we employ a methodology from the field of epidemiology to measure how quickly this disease can spread throughout a society. We find that in our current fragile market, advice by influential Mavens for underwater homeowners to exercise their put option could result in a flood of strategic defaults causing a contagious downward spiral of residential real estate prices. Asymmetrically, when Mavens recommend homeowners not default, their ability to save a failing market is far more limited.

Keywords: foreclosure contagion, strategic mortgage default, social networks, epidemiology

JEL Classification Codes: C63, C73, G17, Z0
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Introduction

The current global recession began in the U.S. housing market and quickly spread across international financial markets when widespread misuse of improperly rated Credit Default Swaps (CDS) and synthetic CDS on mortgage-backed securities was exposed\(^1\). While over a trillion dollars in government bailout funds have been allocated to lending institutions to stem the tide of defaults and resolve the current foreclosure crisis, very little of that money has resulted in successful workouts of mortgage terms (Edmans, 2012). As a result, there is a new and more dangerous financial contagion taking root across the country. Frustration with the government and with lenders, continued falling home prices, and the prospect of being underwater\(^2\) for many years to come has caused countless homeowners to voluntarily default on their mortgage (Guiso, Sapienza, and Zingales, 2012). The number and percentage of strategic defaults has risen sharply as of late resulting in an unhealthy backlog of cases within the already inundated court systems across the country (White, 2010; Wyman, 2010; Fannie Mae, 2012; and Seiler et al. 2012)\(^3\). Such delays in resolving the housing crisis have further increased the economic incentive for homeowners to stop paying their mortgages. If this moral hazard problem is allowed to continue, the global recession currently experienced could become much more severe moving forward.

If previously cited studies are correct in suggesting that the strategic default decision goes beyond purely economic considerations, then alternative models must be constructed to understand future homeowner decision-making with regards to the decision to exercise the put
option on their mortgage. As social animals, humans knowingly or otherwise look to their peers before reaching financially life-altering choices. As such, we recognize the need to factor into our understanding the social aspects of this critical decision⁴. To model the social aspect⁵ of the decision to strategically default, we integrate a social network component into an agent-based model (ABM) framework. We theorize that the burgeoning advocacy of strategic default can be likened to a disease, and measure how quickly this disease can spread throughout a society. At the same time the disease is spreading, a treatment is released⁶, and the relative rate of transmission through the social network is measured resulting in either a full market recovery or a complete collapse of the financial system. From an epidemiological perspective, this is a very typical approach when attempting to prevent the further spread of a disease. From an economic perspective, this methodology has never before been adopted⁷. The novelty of our approach to understand strategic default and its effect on the housing market, and therefore the overall economy, is made possible by merging theories from both economics and epidemiology.

Social network models are more inclusive than pure biological contagion models in that biological models require a physical mode of transmission from an infectious individual to a susceptible individual in order for a disease to spread. In network-based models, an infectious agent can spread through proximity (face-to-face interactions such as bumping into a neighbor while checking the mail, seeing a friend at the grocery store, and so forth), but it may also be transmitted over social media such as telephones, email, Facebook, TV, radio, newspapers, etc. In this sense, we extend the work of Engelberg and Parsons (2011) who examine the causal impact of media on financial markets⁸. Housing pundits, or real estate Mavens, share their expert opinion with a large audience on a very frequent basis through such media outlets as television,
newspapers, Twitter, and so forth. These social networks create the potential for much faster disease spread/cure than in the past. The extent to which real estate experts, or Mavens, can slow or speed the spread of a social disease might also be a function of the expanse of their social networks. For example, real estate Mavens with a nationally syndicated radio or television show have a greater ability to impact societal beliefs than a college professor who is a Maven known only to her students and possibly the immediately surrounding community. In addition to the importance of the sender of the signal, it is also important to measure the receptivity of the person receiving the information. To what degree are people receptive to the concept that it is acceptable to strategically default on ones mortgage? Finally, our epidemiological model incorporates the social connectivity of the infected party. Analogous to a biological disease, individuals who are isolated from the rest of society can do little to infect others. As such, they can do little to further spread the outbreak of the advocacy of strategic default.

Our model shows that real estate experts can greatly impact mortgage markets through their use of behavioral advocacy. In fragile markets, advice by influential Mavens recommending homeowners stop paying their mortgage can result in a flood of strategic defaults causing a contagious downward spiral of home prices. Interestingly, Mavens’ ability to restore a failing market is much lower. Overall, disposition time is the most important financial variable on which to focus to prevent a housing market collapse, while susceptibility to normative influence (SNI) is the most critical component from an epidemiological standpoint. A reduction in foreclosure disposition time is best handled by policymakers who can streamline the legal arena surrounding
the foreclosure process and get real estate owned (REO) homes out of the banks’ hands and back into the legal possession of a healthy buyer. Concerning SNI, existing government programs such as the National Foreclosure Mitigation Counseling program and HUD-sponsored programs should incorporate into their existing programs efforts to educate and dissuade homeowners from choosing the strategic default option.

Predicting mortgage defaults

Historically speaking, mortgage default models are typically designed using a dual trigger approach where the first trigger is a shock to the homeowner’s income stream. This interruption in cash flow might be the result of being laid off at work, getting divorced, becoming ill, or even passing away. Once an inability to pay has occurred, the second trigger relates to the equity position in the home. If the borrower has equity in the property, it makes sense to sell the home, pay all associated fees, and retain the difference. However, if the borrower owes more to the lender than the sale of the home will yield, then there is a chance he does not have the money to pay back the deficiency. This does not necessarily mean the borrower will default. The homeowner can use funds from any number of sources to compensate for the negative equity position (e.g., a savings account, borrowing from family/friends or accessing capital through credit cards, and so forth).

When faced with a deficiency and the ability to pay off the outstanding loan balance, the borrower must then decide if it is in his best interest to do so. If the borrower does pay off the mortgage by borrowing from an outside source, it is most likely that the new loan will have a higher interest rate. If the homeowner decides to default on the mortgage (or is otherwise unable
to pay off the loan), then he will face severe financial consequences of breaching his mortgage contract. Penalties include a severe reduction in his credit score\textsuperscript{10}, difficulty in obtaining future credit, a higher cost when borrowing money in the future, and so forth.

In a strategic default situation, the first trigger of the two trigger model is different. That is, the homeowner does not experience an income shock that necessitates a choice of whether or not to default on the loan. Instead, the borrower becomes aware of his negative equity position and then performs a series of financial and emotional calculations to decide whether or not to default on his mortgage. Recently, the overwhelming media coverage of the current financial crisis has made homeowners aware - or at least alerted homeowners to become aware - of their equity position in the home (the first trigger). Moreover, several market Mavens, many of whom have national outlets to share their opinions such a syndicated radio or television show, newspaper column, blog, or website, have advocated the financial benefits of strategically defaulting (the second trigger). While the merits of such a choice can and will continue to be debated, what is indisputable is that the option to strategically default has certainly been brought to the attention of current homeowners like never before in our history.

Guiso, Sapienza, and Zingales, (2012), White (2010), and Seiler et al. (2012) have informed our understanding of the drivers behind a homeowner’s decision to strategically default. Specifically, fear of financial backlash, shame, and guilt are all factors which cause a homeowner to resist strategic default, while anger with the lender, a pessimistic outlook regarding future home prices, morality, and of course, being “underwater” on the mortgage are the drivers that tip the scales in favor of strategic default. State-specific bankruptcy exemption levels and real estate laws do not
significantly explain the decision to strategically default, in part because the decision to walk away from a mortgage is emotional, but also because the relevant laws are uncertain and confusing to distressed borrowers (Ghent and Kudlyak, 2011).

What is clear is the existence of foreclosure contagion – the negative impact that the foreclosure of a single home has on the home prices of surrounding properties. This effect has been widely studied and clearly documented over the last five years (Immergluck and Smith, 2006; Harding, Rosenblatt and Yao, 2009; Lin, Rosenblatt and Yao, 2009; Rogers and Winter, 2009; Ding et al. 2011; Daneshvary, Clauretie, and Kader, 2011; An and Qi, 2012; and Goodstein et al. 2012).

While estimates of the severity of the foreclosure contagion effect vary, it is clear that asset prices in the residential real estate market are heavily linked across both time and distance when negatively impacted by a foreclosure.

A Review of the Social Network Literature

It is becoming increasingly clear in a variety of fields that individual decision-making cannot be understood without exploring the influence of the social groups to which the individual belongs. As fundamentally social animals, humans look to their peers (whether knowingly or based on subconscious instinct) in forming their opinions, habits, and behaviors (Dalkey 1969; Holyst et al. 2000; Seiler, Lane, and Harrison 2012). In some cases, these effects are obvious (e.g. peer pressure among teenagers, Brown, Clasen and Eicher 1986); however, some much more subtle effects have been shown to be no less critical to individual outcomes (Kohlera and Bühler 2004, Christakis and Fowler 2007). In many fields, studies of how the simultaneous processes of social contact and group behavior influence individual decision-making, and how individual decisions
contribute to the dynamics of the group have revealed some critical ‘tipping points’ in communication, group structure, and particular global outcomes that are inaccessible to explanation by methods that failed to include these social effects (Glaeser and Scheinkman 1996, 2003; Grabowski 2009). By studying these processes of social interactions quantitatively, and modeling these bidirectional and highly interdependent influences, we can achieve a much more complete understanding of decision-making, even for seemingly very individual, independent decisions (Scherer and Cho 2003; Hong, Kubiak, and Stein 2004, 2008). When exploring the emergence of group-level outcomes from individual beliefs and actions, many fields have adopted techniques of Social Network Analysis (SNA) to explore how the processes of social influence shape those emergent properties.

Fundamentally, SNA is a set of quantitative tools to explore global structures and individual roles in social groups. These tools have a relatively brief history of development and application across a diversity of fields. The first rigorous developments of network characterization in the social sciences can be traced back as far as the 1930’s (Borgatti et al. 2009), however, the methods and perspectives which contribute to current quantitative research borrow from areas of physics and applied mathematics developed much earlier for different purposes (Wasserman and Faust, 1994; Albert and Barabási, 2002; Chartrand and Lesniak, 2005). The main goals of these methods are to understand the nature of social interactions beyond those immediately observable by direct contact tracing. Metrics have been introduced to quantify the relative importance of individuals within social networks under a variety of definitions (e.g. degree, closeness, betweenness, and many others; cf. Freeman 1979), and similarly to quantify the levels of complexity or sophistication in global network organizations (Freeman 1979). The nature of the
quantitative metrics developed to study network structure and organization on both individual and global network levels are as varied as the applications for which they were designed. Especially throughout the past decade, interdisciplinary attention to social network methods has led to a number of fascinating applications in such areas as sociology (Freeman, 1979; Burt, 1980), psychology (Brissette, Scheier, and Carver, 2002; Zohar and Tenne-Gazit, 2008), biology (Fraser et al. 2002; Proulx, Promislow, and Phillips, 2005; Fefferman and Ng 2007a), epidemiology (Fefferman and Ng 2007b, Meyers 2007), marketing (Reingen et al. 1984, Haenlein 2010), management (Glaeser and Scheinkman 1996, 2003; Sparrowe et al. 2001; Brass et al. 2004), and finance (Hong, Kubiak, and Stein 2004, 2008) among others.

Some studies have explored the socially generated spread of belief without the explicit topological structure of a network. Relying on empirical observation to characterize the spread of fear and the determination of socially appropriate reactions to unknown threats, Lofgren and Fefferman (2007) followed the reactions of players in a massively multiplayer online role playing game, Blizzard’s World of Warcraft, to the accidental introduction of a deadly epidemic. Social contacts and conversations were found to play a profound role in each individual’s understanding of the purpose of and risks from the disease itself. During the outbreak, individuals relied on socially generated norms and beliefs to determine appropriate courses of action to take in response to the epidemic. While some players were ‘griefing’ (i.e. behaving in ways to purposefully inconvenience and/or annoy other players), some were attempting to respond with socially responsible actions (i.e., healing or warning others, spreading the word about an attempted quarantine, etc.). More interestingly, social norms ‘punished’ some of those who had ‘behaved badly’ during the outbreak, infecting fellow guild-members (i.e., colleagues
within the game) or failing to help weaker party members (immediate collaborators - these groups of collaborators are usually long-term friendships, lasting months, or even years).

Individuals holding belief about whether or not these behaviors are appropriate within the society of the game world could be expected to be influenced by these reactions in any future risk scenarios, thereby updating their beliefs in response to those of their social contacts, and converging on within-virtual-world norms of acceptable behavior.

The mathematics of the spread of beliefs and the importance of individual influence is itself constantly expanding. Grabisch and Rusinowska (2010) recently analyzed a model in which an individual has an inclination, or belief, towards some decision of either “Yes” or “No”, however where there is the potential for difference between belief and action. By separating and analyzing individual influence from the emergent decision of the group, they expanded the mathematical toolkit for determining the influence of individuals in networks.

In sum, social network models are becoming increasingly popular in explaining observed behavior in a number of fields. By understanding this behavior, social networks therefore simultaneously point towards a solution to these same problems. In this study, we incorporate social network modeling into an existing traditional economic foreclosure contagion model in an attempt to identify the social network factors that contribute to the overall health or collapse of the residential real estate markets, and therefore, the financial markets at large.

**An Economic Agent-Based Model**
Gangel, Seiler, and Collins (2012) constructed a purely economic simulation model of the U.S. housing markets to examine mortgage foreclosure contagion and its impact on home prices. Here we briefly describe the three core components of their ABM framework. The first main function is the appraisal process which is necessary to calculate each month to track home price levels across the market. The appraisal process the authors use is reflective of how actual appraisals are performed. Only sales within the last six months and within a certain radius are used to estimate the value of the subject property\(^{11}\). Similar to a reconciliation statement, the model gives a greater weight to sales that occur closer in both time and proximity to the subject property.

The second main function within the economic model is the default function. After the value of the property has been measured, four factors are used to determine if the property goes into default. The first factor is the amount of negative equity in the home. The deeper the home is underwater, the greater the probability of default. The second factor is a potential payment shock. Because a historically reflective percentage of the properties are financed with adjustable rate mortgages (ARMs), it is possible that when the rate adjusts, the result is an unaffordable increase in mortgage payment\(^{12}\). Each of the 2,500 homes within the market is associated with a unique amortization schedule\(^{13}\). Moreover, each ARM resets at potentially different months within the model. Thirdly, the model accounts for the default probability difference between investors and owner occupants reflecting the historical observation that investor loans are riskier in terms of default probability. Finally, income shocks are considered such as job loss or income curtailment, prolonged illness, death, and divorce.
The third major component within the economic model is the sales function. Based on the seminal work of Genesove and Mayer (2001), whose explanation was subsequently modified in Sun and Seiler (2012), the author’s model considers false reference points and the contemporaneous equity position of the potential seller before determining which agents within the model wish to list their homes for sale. As a result, while all properties have a chance to be listed, those with positive equity and those above their initial purchase price have an increased probability of being listed. Local market competition is also considered within the model. Sales prices decrease when the market is associated with a greater number of homes listed for sale and vice versa. Once a property sells, a new set of agent characteristics are assigned to the home consistent with historical values observed in actual housing markets. Inputs used in their model as well as the new social network inputs are reported in Exhibit 1.

A Social Network Agent-Based Model

We greatly extend the Gangel, Seiler, Collins economic model by integrating social network components to measure the differential effects that media and society play in determining pricing behavior in the housing markets. To capture how personal beliefs, especially about socially generated norms, are formed and maintained in this spatial financial setting, we employ a slightly modified standard network-based model of influence and opinion formation (Friedkin and Johnsen 1990). The mathematical framework for such a model can be defined generally as an iterative process on a set of \(n\) homeowners, 2500 in our simulation, who each hold a belief at each point in time. In this basic formulation, at time 1:

\[
Y_1 = X_1 B_1
\]  
(Eq. 1)
where, $Y_t$ is an $n \times 1$ vector of beliefs, $X_t$ is an $n \times k$ matrix that represent each of $k$ external factors relevant to each individual’s opinion, and $B_1$ is a $k \times 1$ vector representing the relative impact of each of the external factors on opinion formation (held constant over all individuals). $Y_t$ is an $n \times 1$ vector of beliefs held by the $n$ individuals in the population at time $t$; the beliefs are normalized between $[0, 1]$. In subsequent time steps in this model, the current beliefs of individuals $Y_t$ for time $t = 2, 3, \ldots$, are revised based on the influence of others in a network to whom individual $n$ is connected, in addition to the direct response of individuals to the $X_t$ external factors. This model is a Markov process (Gardiner 1985), in which only the opinions in the immediately previous time step influence current opinion according to the following equation:

$$ Y_t = \alpha_t W_t Y_{t-1} + \beta_t X_t B_t $$  \hspace{1cm} (Eq. 2)

where $Y_t$, $X_t$, and $B_t$ are defined as in (eq. 1), $\alpha_t$ is the relative weight of the importance of prior beliefs in the population on shaping current opinions, $\beta_t$ is the equivalent relative weight of importance of the external factors, and $W_t$ is an $n \times n$ matrix that describes the linear system of equations transforming all opinions in the previous time step, $t - 1$ to the $n$ opinions held at time $t$. Equation 2 is applied recursively to project the changing opinions held by the members of the population over time.

We then tailor the model to investigate our hypothesized influence of socially generated belief regarding strategic default behavior for mortgages. How these beliefs translate into actions is
then determined by the relationship between belief and external economic factors from the original model\textsuperscript{16}, called Forenet, without belief (i.e., current market price for owned property, current value of debt owed on the property, and so forth). Building directly from the Forenet model, we eliminate the external factors from influencing ongoing formation of belief structure, instead focusing only on the socially driven processes of belief update. We therefore also eliminate an $\alpha_z$ term, by setting it equal to one, since there is no $\beta_z$ from a $\beta_z X_z B_z$ term against which the relative value would be judged. Thus, Equation 2 is simplified to $Y_z = W_z Y_{z-1}$. We adjusted our model to discount the impact of beliefs of social contacts who own property further away relative to those of social contacts who own property close by. We further allow for the inclusion of some individuals who carry greater weight among their peers when it comes to influencing future decision-making (i.e., Mavens). Alternatively stated, a Maven’s beliefs have a greater impact on others, once communicated.

Based only on socially generated belief processes, we generate a both spatially and socially driven belief structure as our equivalent of the $W_z$ matrix to reflect two levels of social influence we believe to be most directly important to forming beliefs about strategic default behavior: the beliefs of those in the immediate spatial neighborhood (as owners of property whose values and actions will directly affect the property of the individual evaluating his/her beliefs), and the beliefs of friends/family/social networks outside of the immediate vicinity of the individual’s property, but still within the larger community of property owners. (While the matrix notation remains valid, from this point, we instead will present the actions of the belief process on each individual $n$’s belief, $y_{n,z}$, which is the $n^{th}$ element of the $Y_z$ vector.)
Social Network
In our model, to initialize the population’s belief states at \( t = 1 \), we set \( Y_1 \) as a vector of independent values, assigned according to an experimentally determined distribution (Seiler 2012, and Seiler, Lane, and Harrison 2012). We define a distance symmetric matrix, \( \Delta \), where \( \delta_{i,j} \geq 0 \) is the distance from the property held by \( i \) to the property held by \( j \) in the spatially explicit Forenet model; thus, if \( i \neq j \) then \( \delta_{i,j} > 0 \). We then define an interaction network represented by an \( n \times n \) matrix, \( \Theta \), where each entry \( \theta_{i,j} \) represents the social connection between individual \( i \) and individual \( j \). \( \theta_{i,j} \) is a Boolean value where ‘\( \theta_{i,j} = 1 \)’ represents the existence of social connection between individual \( i \) and individual \( j \) and ‘\( \theta_{i,j} = 0 \)’ whenever no connection exists between the individuals (note, therefore, \( \theta_{i,i} = 0 \)). We define a social connection to involve at least two individuals; thus, an individual has no social connectivity with themselves, \( \theta_{i,i} = 0 \). To populate the values of this matrix \( \Theta \), we define a neighborhood within a spatial radius, \( r \), and \( \forall j \mid \delta_{i,j} < r \), \( \theta_{i,j} = 1 \). Thus, \( r \) is spatial radius around an individual’s property within which we assume social connection due to neighborhood/proximity. Note that ‘\( \delta_{i,j} = \delta_{j,i} \)’. The properties are distributed in a uniform grid fashion within our simulation model; thus, a spatial radius was selected to produce a Manhattan (or Von Neumann) neighborhood, i.e., a neighborhood consisting of four closest properties.

To include the second level of social connectivity, motivated by family, friendship, and broader social networking rather than those connections determined by spatial proximity, we defined, \( \psi_i \), which determines the relative measure of social connectivity of each individual ‘\( i \)’. Let \( \psi = \{\psi_1, \psi_2, ..., \psi_n\}^T \) be the vector of all such social connectivity for the ‘\( n \)’ properties. The
distribution of $\psi_i$ for the population is informed by Seiler (2012). There is also a global social connectivity weighting, $\psi$; this weighting is varied through sensitivity analysis in the simulation results. The following procedure is used to determine the initial social connections of the individual agent-properties within the simulation.

The probability of social connectivity between two individuals is determined by both individuals, thus we first determine the social connectivity symmetric matrix $P = \{p_{ij}\}$:

$$P = 0.5 \times \psi \times \psi^T$$  \hspace{1cm} (Eq. 3)

In this way, $P$ captures the pairwise interaction of individual beliefs from each element of $\psi$, scaled both by the probability of the existence of social contact and by the relative importance of that contact, should it exist. The ‘0.5’ comes in as each pair of individuals will check to see if they are connected, with the same probability $p_{ij} = p_{ji}$. To avoid this doubling up, the matrix ‘$P$’ is converted into an upper triangular matrix ‘$P*$’ as follows:

$$p_{i,j}^* = \begin{cases} 0 & \text{if } i \geq j \\ 1 & \text{if } i < j; \delta_{ij} \leq r \\ 2p_{ij} & \text{o/w} \end{cases} \hspace{1cm} (Eq. 4)$$

This new matrix only gives the probability that each pair of individuals is connected once, the other possibility being replaced with a probability of zero. Now consider a stochastic matrix ‘$U = \{u_{i,j}\}$’ such that each element has a standard uniform distribution, ‘$u_{i,j} \sim U(0,1)$.’ We then define matrix ‘$Q = \{q_{ij}\}$’ such that:

$$q_{i,j} = \begin{cases} 1 & \text{if } p_{i,j}^* > u_{i,j} \\ 0 & \text{o/w} \end{cases}$$
If \( i < j \), the matrix ‘Q’ only shows whether ‘j’ is connected to ‘i’ but does not show if ‘i’ is connected to ‘j’. The transpose of ‘Q’ will show the connection the other way; thus, the interaction network is now simply defined as the matrix \( \theta = Q + Q^T \).

Once an individual, \( k \), sells or has his property foreclosed, he is “replaced” in the network with a new buyer\(^{17} \). In other words, a new individual, \( k \), with the same values \( \delta_{k,j} \forall j \) but was assigned a new set of Forenet mortgage characteristics and a new random value for ‘\( \psi_k \)’. Using the new ‘\( \psi_k \)’ value, the individual’s social network is randomly determined, using a similar methodology to what is given above and the matrix ‘\( \theta \)’ updated to reflect this.

**Mavens**
To explore the impact of inclusion of the influence of acknowledged experts, the top 12% of most influential individuals from the data set were chosen to be Mavens. The dataset was split into two: mavens and non-mavens. When an individual was initialized and determined to be maven/non-maven, their characteristics were randomly draw from the appropriate data set. Thus, different ratios of mavens to non-mavens can be considered using this process and datasets.

**Belief updates**
At each time step within the simulation run, each ‘\( i \)’ individual’s beliefs are updated based on the influences of those ‘\( j \)’ individuals in their social network. There are multiple factors that affect this update, namely: ‘\( s_z \)’ which is the susceptibility to normative influence for each individual ‘\( i \)’ and ‘\( \mu_j \)’ which is the relative influence of individual ‘\( j \)’ over their peers in the social network. Both values are normalized to \( (0, 1] \). ‘\( h \)’ is the relative importance of the previous beliefs of others relative to one’s own prior beliefs (for purposes of our analysis, \( h = 0.06 \))\(^{18} \), and ‘\( S \)’ and
‘$s_i$’ are defined as the weight of the susceptibility to normative influence in the network, and the individual susceptibility, respectively (Seiler 2012; and Seiler, Lane, and Harrison 2012); both values are normalized to (0, 1]. These values are combined in an exponential smoothing fashion to determine the update of the individual’s belief over time:

$$y_{i,t+1} = (1 - h \cdot S \cdot s_i) y_{i,t} + h \cdot S \cdot s_i \sum_{j \neq i} \left( \frac{\mu_j \cdot \delta_{i,j} \cdot y_{j,t}}{\delta_{i,j}} \cdot \frac{1}{\sum_{j \neq i} \mu_j \cdot \delta_{i,j} / \delta_{i,j}} \right)$$  \hspace{1cm} (Eq. 5)

This updating equation has two parts. The first part is how much an individual’s belief stays the same, and the second is how much it is influenced by their social network. The second part is a weighted average of beliefs of all the individual’s peers. We define this average as ‘$X_i$’ as given in Equation 6. The weighting comes from both the influence ‘$\mu_j$’ and distance ‘$\delta_{i,j} > 0$’ of these peers. ‘$\theta_{ij}$’ ensures that only peers in the individual’s social network are considered.

$$X_{i,t} = \frac{1}{\sum_{j \neq i} \mu_j \cdot \theta_{i,j} / \delta_{i,j}} \cdot \sum_{j \neq i} \left( \frac{\mu_j \cdot \theta_{i,j} \cdot y_{j,t}}{\delta_{i,j}} \right)$$  \hspace{1cm} (Eq. 6)

In the language of the general model, this equation populates the matrix $W_z$ such that the diagonal entries are equal to ‘$1 - S \cdot s_i \cdot h$’ and the off-diagonal entries are set equal to

$$\left( \frac{\mu_j \cdot \theta_{i,j}}{\delta_{i,j}} \cdot \frac{1}{\sum_{j \neq i} \mu_j \cdot \theta_{i,j} / \delta_{i,j}} \right).$$

Since each of the members of an individual ‘$i$’ social network has the potential to impact the belief of the individual. The impact of the members is determined by their relative influence and their distance from the individual under consideration; thus, their belief is weighted by ‘$\mu_j / \delta_{i,j}$’. The average, $X_{i,t}$, of all these weighted terms is taken as shown in equation 6 where the ‘$\theta_{i,j}$’ terms ensure that only members of the ‘$i$’ individual’s social network are consider.
There are various properties relating to this update that must be proven. The first lemma considers what value the update, $X_{i,t}$, would have if all those members in the social network have a belief of one.

**Lemma 1:** If $y_{j,t} = 1$ $\forall j$ s.t. $\theta_{i,j} = 1$ and $\exists k \neq i$ s.t. $\theta_{i,k} = 1$ then $X_{j,t} = 1$

**Proof:** Since $\mu_{i}$, $\theta_{i,j} \geq 0$ and $\delta_{i,j} > 0$ for $j \neq i$ then $\frac{\mu_{i,j} \cdot \theta_{i,j}}{\delta_{i,j}} \geq 0$ for $\forall j \neq i$

Since $\mu_{k}$, $\delta_{i,k} > 0$ then $\frac{\mu_{k} \cdot \theta_{i,k}}{\delta_{i,k}} > 0$, $\therefore$ $\sum_{\forall j \neq i} \mu_{j} \cdot \theta_{i,j} / \delta_{i,j} > 0$

If $\theta_{i,j} = 0$ then $\frac{\mu_{j} \cdot \theta_{i,j} \cdot y_{j,t}}{\delta_{i,j}} = 0$ for $\forall j \neq i$

If $\theta_{i,j} = 1$ then $\frac{\mu_{j} \cdot \theta_{i,j} \cdot y_{j,t}}{\delta_{i,j}} = \frac{\mu_{j} \cdot \theta_{i,j}}{\delta_{i,j}}$ for $\forall j \neq i$

Since $\theta_{i,j} \in \{0,1\}$, $\frac{1}{\sum_{\forall j \neq i} \mu_{j} \cdot \theta_{i,j} / \delta_{i,j}} \cdot \sum_{\forall j \neq i} \left( \frac{\mu_{j} \cdot \theta_{i,j} \cdot y_{j,t}}{\delta_{i,j}} \right) = \frac{1}{\sum_{\forall j \neq i} \mu_{j} \cdot \theta_{i,j} / \delta_{i,j}} \cdot \sum_{\forall j \neq i} \left( \frac{\mu_{j} \cdot \theta_{i,j}}{\delta_{i,j}} \right) = 1$

QED.

Therefore, Lemma 1 demonstrates that if all members in the network have a belief of one, then the updated average, $X_{i,t}$, is also one. This is what would be expected. Consider now the case when all have a belief of zero.

**Lemma 2:** If $y_{j,t} = 0$ $\forall j$ s.t. $\theta_{i,j} = 1$ and $\exists k \neq i$ s.t. $\theta_{i,k} = 1$ then $X_{j,t} = 0$

**Proof:** from above, $\sum_{\forall j \neq i} \mu_{j} \cdot \theta_{i,j} / \delta_{i,j} > 0$

Since $\theta_{i,j} \in \{0,1\}$, $\theta_{i,j} \cdot y_{i,t} = 0$ for $\forall j \neq i$

$\frac{\mu_{j} \cdot \theta_{i,j} \cdot y_{i,t}}{\delta_{i,j}} = 0$ for $\forall j \neq i$, $\therefore$ $\sum_{\forall j \neq i} \left( \frac{\mu_{j} \cdot \theta_{i,j} \cdot y_{i,t}}{\delta_{i,j}} \right) = 0$, $\therefore$ $X_{j,t} = 0$

QED.
These two lemmas convey that in the extreme cases of belief, when all social network members believe the same extreme, then the individual’s beliefs will be updated towards that extreme as would be expected. Together, they provide the boundary conditions on the system. It remains then to prove a final lemma to ensure our updating mechanisms will keep the individual’s belief between the extremes.

**Lemma 3:** if \( \forall i \exists k \neq i \text{ s.t. } \theta_{i,k} = 1 \) then \( y_{i,t} \in [0,1] \ \forall i, t \)

Proof (by induction): \( t = 1 \), by definition, \( y_{j,1} \in [0,1] \ \forall i \)

Consider true for \( y_{j,t} \in [0,1] \ \forall i, t \)

Since \( \delta_{i,k} > 0 \) and \( \forall i \exists k \neq i \text{ s.t. } \theta_{i,k} = 1 \) then the following formula is well-defined:

\[
y_{i,t+1} = (1 - h \cdot S \cdot s_i) y_{i,t} + h \cdot S \cdot s_i \sum_{j \neq i} \left( \frac{\mu_{j, i} \cdot \theta_{i,j} \cdot y_{i,t}}{\delta_{i,j}} \cdot \frac{1}{\sum_{k \neq i} \mu_{j, i} \cdot \theta_{i,j}} \right)
\]

Since \( \mu_i, \theta_{i,j} \geq 0 \); \( \delta_{i,j} > 0 \); \( S, s_i, h \in [0,1] \) and \( y_{j,t} \leq 1 \) then:

\[
y_{i,t+1} \leq (1 - h \cdot S \cdot s_i) + h \cdot S \cdot s_i \sum_{j \neq i} \left( \frac{\mu_{j, i} \cdot \theta_{i,j} \cdot 1}{\delta_{i,j}} \cdot \frac{1}{\sum_{k \neq i} \mu_{j, i} \cdot \theta_{i,j}} \right) = (1 - h \cdot S \cdot s_i) + h \cdot S \cdot s_i = 1
\]

Since \( \mu_i, \theta_{i,j} \geq 0 \); \( \delta_{i,j} > 0 \) and \( y_{j,t} \geq 0 \) then:

\[
y_{i,t+1} \geq (1 - h \cdot S \cdot s_i) \cdot 0 + h \cdot S \cdot s_i \sum_{j \neq i} \left( \frac{\mu_{j, i} \cdot \theta_{i,j} \cdot 0}{\delta_{i,j}} \cdot \frac{1}{\sum_{k \neq i} \mu_{j, i} \cdot \theta_{i,j}} \right) = 0
\]

\[\therefore \ y_{i,t+1} \in [0,1]\]
Since, within the simulation, at least four neighbors are in an individual’s social network, these existence assumptions are satisfied for all three lemmas. Thus, the lemmas show that our exponential smoothing updating formula is well-behaved and performs as expected at the extremes.

**Belief Impact**

In each time, $t$, each individual, $i$, evaluates his property value, and decides whether to make his property available for sale. If his property is underwater, then he decides whether or not to default based on the sum of his initial probability to default from the Forenet model and the value of his current belief, $y_{i,t}$, and updates his belief as defined above. Thus, an individual with a belief of one will always default if underwater and an individual with a belief of zero will never strategically default, though he might economically default for other reasons, e.g., a catastrophic event. Based on these definitions and equations, the simulation is then allowed to evolve over time, indicating instances of foreclosure and housing prices based on the dynamics of both the belief network and the economic model.

**Data**

All historical macroeconomic data relating to the underlying ABM mortgage foreclosure contagion model (historic interest rates on ARMs and FRMs, the percentage of FRMs, and the percentage of owner-occupant loans) are from Freddie Mac as discussed in Gangel, Seiler, and Collins (2012). Concerning the social network component of our epidemiological model, the three needed variables are: degree of Mavenism, susceptibility to normative influence, and degree of social connectivity. The rate of disease spread is a function of the level of contagion in

QED.
a diseased person who has contact with previously unaffected individuals: if a diseased person is highly contagious, the transmission of the disease is more likely. This trait describes a “Maven” as a person who is an expert in real estate. Mavens are more contagious than non-Mavens because people place greater trust in their opinions.

Susceptibility to normative influence is a measure of how easily a person can be swayed to change his position on a certain topic. The more easily a person’s opinion can be changed, the faster the disease/cure can spread. A final variable that will be considered is social connectivity. Those who have larger social networks are better able to spread the disease/cure simply because they come in contact with greater numbers of people. Exhibit 2 displays two individual’s social connections. The red pathways reflect the most isolated household in our model with just four connections in their immediate surroundings. The blue lines show a typical household within the model with connections to those in their immediate vicinity as well as several individuals across the neighborhood and across town. Within the simulation, the probability that two individuals are connected is weighted by the distance between the households. The closer two households are together the more likely they will be socially connected. To extend this visualization, imagine seeing the connections of all 2,500 households in our model at one time. This picture is shown in Panel A of Exhibit 3. To make sense of the picture, in Panel B, we zoom in to see the connections of a very social individual within the model.

**Results**

The results from the simulation runs are presented as a series of graphs given in Exhibits 4-9. A three-dimensional graph format was chosen because the majority of results relate to comparing
how two different variables (x-axis and y-axis) affect average house prices (z-axis). The graphs are made up of a set of discrete data points (usually 121), but are displayed on a continuous curve to aid in reader visualization.

Exhibit 4 reports the results from our financial model of foreclosure contagion without the social network components included. We start here to be sure our model is in concert with that of Gangel, Seiler and Collins (2012). Consistent with their model, this “lake and mountain” graph demonstrates that, over historically observed foreclosure discount values and disposition times, disposition time has a greater impact on the rate of foreclosure contagion than does foreclosure discount. With confirmation that the Gangel, Seiler, and Collins (2012) model has been replicated, we next incorporate the social network variables.

The lake and mountain graph can be broken up into three key areas. The first is the peak of the mountain. This area represents simulation runs where the ending average value of households in the model is the greatest. More simply, this is the region where the model does not crash. Intuitively, this makes sense because this is where the foreclosure discount and disposition time is lowest. The lake portion of the graph is where foreclosure discount and disposition time are the greatest. The result is a model that crashes every time. Finally, the shoreline in the lake and mountain graph represents the threshold between surviving and crashing markets. Because the simulation is stochastic, chaotic behavior around the shoreline area is observed resulting in a mix of both crashing and surviving housing markets. It is only within this shoreline region that the social network variables make a difference.
To demonstrate this claim, we begin by performing a series of simulation runs in the mountain region. Specifically, Exhibit 5 shows the relationship between social connectivity and SNI across 121 combinations of 200 simulation runs each (for a total of 24,200 simulation runs). Notice that the flat surface confirms our statement that in good real estate markets, people’s degree of SNI and the extensiveness of their social connections do not crash a market. And this is exactly what we expect to be true. Intuitively, if home prices are going up and the few foreclosed homes that do come onto the market get resolved quickly, social connections and susceptibility to the opinion of those around us would reinforce the prosperity facing the real estate market.

The same graph could be shown for an extremely catastrophic market (one that is in the lake region of Exhibit 4). In a terrible real estate market facing eminent collapse, the extremely negative economic drivers will overcome any reasonable level of optimism that can be spread throughout a social network. Simply stated, in such a poor real estate market, wishful thinking and optimism will not be enough to bring the market back to health. In sum, for extremely negative economic climates, it does not matter on how many social network or economic variables we perform a sensitivity analysis, the result will always be a complete, non-recoverable collapse of the housing market.

With these boundaries understood, it is clear that all useful analysis and understanding of key economic and social network variables must be conducted at or near the shoreline of the lake and mountain graph. With this in mind, we focus our attention on the relative strengths of the three social network variables in shoreline conditions (i.e., in fragile residential real estate markets). As previously mentioned, the shoreline conditions lead to chaotic results from the simulation...
runs. One particular run might result in a market crash, while another might reflect strong growth. It all depends upon the inputs selected for each variable in the model. Following the geographic analogy, if one went down to the seaside on any given day it would be hard to predict if the sea would be calm or have large crashing waves. To overcome this variable nature of the results, a large number of simulation runs was conducted for each variable combination and an average of the results was taken. Normally 30 repeats would be considered adequate for the simulation run, but we repeat our simulation runs over 100 times.

Exhibit 6 displays the relationship between SNI and the degree of people’s connectivity. The graph is made up of 121 (11 x 11) points each replicated 150 times (a total of 18,150 simulation runs conducted over a 1,000 month period for each run). Since the graph slopes more from left to right than from front to back, this demonstrates that SNI contributes more strongly to the health of home prices than does the degree of social connectivity. Again, this makes intuitive sense: an individual who is robust to the suggestions of social peers will be influenced less, even by many peers, than one with few peers who is strongly influenced by their opinions. Though it is important to demonstrate that this effect propagates up from the individual to the entire network in our scenarios of interest, the result is not surprising.

SNI and the social connectivity are both represented within the simulation model as weights that affect the relative algorithmic code which, in turn, affect susceptibility and connectivity, respectively. These weights have been scaled to represent the reasonable limits of the variable. For instance, social connectivity directly relates to the number of social contacts of a household;
this ranges from an average of four contacts to an average of 100 contacts over the 2,500 households.

Exhibit 7 performs a similar analysis, but this time SNI is compared with the percentage of the population that is considered Mavens; the graph was made from 13,982 simulation runs. While less definitive, there is more variation in movement left to right than there is from front to back. Again, the conclusion is that SNI is a more deterministic network influencer than is Mavenism. Exhibit 8 rounds out the social network comparisons by presenting an analysis of social connectivity and Mavenism. An interesting “V-shape” appears on the x-axis where the average number of people in household’s social circle is approximately 160. What is so intriguing about this low point is that Gladwell (2002) discusses in his book the notion that there is a societal ideal critical mass below and above which the group does not function as well. Gladwell collects observational data from a number of periods in time and across multiple cultures. The number Gladwell discusses as ideal is a network of 150 people\(^2\). The last three exhibits (6-8) reveal that within the range of historically observed behavior, SNI is the most influential social network variable, followed by social connectivity, and finally Mavenism. While Mavenism is the least influential variable, it is still economically important to the health of the real estate market. To demonstrate this claim, we now turn to a deeper analysis of Mavenism to learn how the strong opinion of a few can influence a fragile (shoreline) real estate market. No study has ever demonstrated or even suggested the percentage of the population comprised by Mavens. In Seiler (2012), Mavenism was measured on a 7-point scale, but no dichotomous delineation was provided to differentiate Mavens from non-Mavens. As
such, we use a series of reasonable cutoffs to classify a certain percentage of people in society who others would consider experts in real estate. In Exhibit 9, we report the outcome of simulations that assume 12% of the people are Mavens.

In Panel A of Exhibit 9, we assign all Mavens the belief that people should strategically default on a mortgage once underwater. When moving in the graph from left to right, we clearly see a substantial downward slope indicating that the more susceptible people are to the Mavens’ influence, the more likely real estate markets are to crash. This result is consistent across all tested social connectivity levels (again supporting the earlier finding that SNI is more influential than social connectivity). Simply stated, a few bad Mavens can bring down an already fragile market.

Panel B reports the results where the Mavens in the sample all believe homeowners should NOT strategically default on a mortgage no matter how far underwater the home is. For the sake of illustration, we begin the simulation under the condition that the non-Mavens in society believe they should default if they are underwater. Looking from left to right in the graph, we see a decline in ending home values at lower SNI weights indicating that if Mavens cannot influence non-Mavens, then the real estate market will crash. However, if people are susceptible to the positive Maven influence (recommending people not strategically default), then the market will be allowed to recover. This exhibit underscores the importance of the Maven influence on other people in the network. From a policy standpoint, it supports the contention that it can be fruitful for policymakers to engage in media campaigns to change social opinion on topics of relevance.
to economic stability. More specifically, if policymakers can convince Mavens, the Mavens will in turn do the work to convince others across society.

Now that the impact of the social network variables on home prices are understood, we next measure the relative strengths of the two key economic variables versus that of the three social network variables. Exhibit 10 reports the results from a regression estimated over the entire sample as well as the results from a regression focused more narrowly on input ranges found to exist in past studies. Standardized betas can be used to determine all five variables’ relative strengths in the model. Both the full and restricted sample results confirm that the order of significance is as follows: disposition time, foreclosure discount, SNI, social connectivity, and finally Mavenism. These results are entirely consistent with the graphs reported earlier in the paper. In sum, while the economic variables are more robust, both the economic and social network variables significantly impact home prices in our model.

**Policy Implications and Conclusions**

Economists warn of an impending double dip in the global recession stemming directly from a failure to recover from the on-going housing crisis. Recent studies argue that strategic mortgage defaults are responsible for this failed market recovery. We agree and add that in addition to financial incentives for walking away from a mortgage homeowners can afford to pay, there are also behavioral aspects to the decision that warrant quantitative considerations. Accordingly, we employ an epidemiological approach to study the outbreak of the burgeoning sentiment that it is socially acceptable to strategically default on one’s mortgage.
We find that disposition time is the most significant economic contributor to a housing market collapse, while SNI is the most significant social network component. That disposition time is important bodes well for policymakers in that the foreclosure process can be streamlined to reduce the total time foreclosed properties are allowed to linger unresolved in the marketplace, thus reducing the foreclosure contagion effect. Likewise, the finding that SNI is the most significant epidemiological variable is important because policymakers can pursue various techniques to change the beliefs about the philosophy of whether or not it is acceptable to strategically default. Ideally, this change in beliefs would begin with real estate Mavens who would then change the beliefs of others in society.

One way to potentially change beliefs surrounding strategic default is to educate the public through Homeownership Education and Counseling (HEC) programs. Collins and O’Rourke (2011) summarize the literature relating to the effectiveness of formal HECs sponsored by both private and public organizations. While HEC program studies suffer from various deficiencies, the general conclusion is that HEC works to increase the success rate of loan modifications and reduce mortgage default rates. In more detail, Collins and O’Rourke (2011) conclude that default rates are most reduced with proactive post-purchase counseling or counseling that takes place within 30 days of late mortgage payments (as opposed to waiting 90 days). After 90 days, it seems the homeowner has already financially and psychologically committed to the decision to default.

If people can be influenced by HECs to avoid economic default, then it seems reasonable to surmise that they can be even more easily influenced not to strategically default (FICO, 2011).
Addressing this strategic default problem might be a topic best covered as part of the existing National Foreclosure Mitigation Counseling program or through the U.S. Department of Housing and Urban Development (HUD). Additionally, White (2010) suggests that the media can be used as a venue for swaying public opinion away from the decision to strategically default. We leave this discussion for future study.
References


FICO, Predicting Strategic Default, 2011, April, white paper.


Acknowledgment

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Exhibit 1. Inputs from the Original Economic Foreclosure Model and the New Social Network Model
This exhibit reports the input estimates and range of values tested in the original economic foreclosure model (Panel A) as well as the new social network variables (Panel B) introduced in the current study.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Point Estimate(s)</th>
<th>Range Tested (if any)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Economic Model Variable Inputs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Starting Home Prices at initiation</td>
<td>$200,000</td>
<td></td>
</tr>
<tr>
<td>Mortgage length</td>
<td>30 years</td>
<td></td>
</tr>
<tr>
<td>Down Payment Percentages</td>
<td>3%, 5%, 10%, 20%</td>
<td></td>
</tr>
<tr>
<td>ARM Interest Rates</td>
<td>Historic, based on MBA</td>
<td></td>
</tr>
<tr>
<td>FRM Interest Rates</td>
<td>Historic, based on MBA</td>
<td></td>
</tr>
<tr>
<td>% of FRM</td>
<td>Historic, based on MBA</td>
<td></td>
</tr>
<tr>
<td>Probability (FRM owner is occupant)</td>
<td>0.9</td>
<td></td>
</tr>
<tr>
<td>Probability (ARM owner is occupant)</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>Time on Market (TOM)</td>
<td>3-9 months</td>
<td></td>
</tr>
<tr>
<td>Percentage of Properties Listed</td>
<td>Home Price Growth &lt; 6%; 2% Sliding scale in between Home Price Growth &gt; 12%; 4%</td>
<td></td>
</tr>
<tr>
<td>Baseline Foreclosure Rate</td>
<td>1%</td>
<td></td>
</tr>
<tr>
<td>Disposition Time (months)</td>
<td>7</td>
<td>3 ~ 11</td>
</tr>
<tr>
<td>Foreclosure Discount</td>
<td>-0.1</td>
<td>-0.01 ~ -0.1</td>
</tr>
<tr>
<td>Panel B: Social Network Variable Inputs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual Susceptibility to Normative Influence (SNI)</td>
<td>Full distribution of values taken from Seiler (2012)</td>
<td>0 ~ 1</td>
</tr>
<tr>
<td>Individual Connectivity</td>
<td>Full distribution of values taken from Seiler (2012)</td>
<td>0 ~ 1</td>
</tr>
<tr>
<td>Mavenism (percentage of population)</td>
<td>12%</td>
<td>0% ~ 30%</td>
</tr>
<tr>
<td>Global Connector Weight</td>
<td>0.05</td>
<td>0 ~ 0.1</td>
</tr>
<tr>
<td>Global SNI Weight</td>
<td>0.5</td>
<td>0 ~ 1</td>
</tr>
</tbody>
</table>
Exhibit 2. Graph Depicting Two Households and their Social Connections

- Individual household / property
- Social connections of highly connected household
- Social connections of poorly connected household
Exhibit 3. Screen Captures of Social Network Connections

Panel A. Overview of the Model’s Social Connective Pathways

Panel B. Zoomed in Image of Highly Connected Household
Exhibit 4. Economic Foreclosure Model – No Social Network Components Added
Disposition Time is the time it takes to resolve a foreclosed mortgage. Foreclosure Discount is the percentage by which the subject property decreases in price as a direct result of being foreclosed upon.
Exhibit 5. Typical Comparison of Social Network Variables in Good Markets

Susceptibility to Normative Influence (SNI) measures how easily people can have their belief changed as it relates to their willingness to strategically default at various stages of being underwater in the mortgage. Social Connectivity measures how many households are within the social circle of each homeowner.
Exhibit 6. SNI Weights and Social Connectivity in a Fragile Market
Susceptibility to Normative Influence (SNI) measures how easily people can have their belief changed as it relates to their willingness to strategically default at various stages of being underwater in the mortgage. Social Connectivity measures how many households are within the social circle of each homeowner.
Exhibit 7. SNI Weights and Mavenism in a Fragile Market
Susceptibility to Normative Influence (SNI) measures how easily people can have their belief changed as it relates to their willingness to strategically default at various stages of being underwater in the mortgage. Mavenism represents the ratio of Mavens to total people in the sample.
Exhibit 8. Mavenism and Social Connectivity in a Fragile Market
Social Connectivity measures how many households are within the social circle of each homeowner. Mavenism represents the ratio of Mavens to total people in the sample.
Exhibit 9. Analysis of the Impact of Good and Bad Mavens in a Fragile Market
Susceptibility to Normative Influence (SNI) measures how easily people can have their belief changed as it relates to their willingness to strategically default at various stages of being underwater in the mortgage. Social Connectivity measures how many households are within the social circle of each homeowner.

Panel A: Bad Mavens in a Fragile Market with Normal non-Mavens

Panel B: Good Mavens with Bad non-Mavens
**Exhibit 10. Regression Results for the Full and Restricted Sample**

This exhibit reports the regression results from two regressions. The first consists of the full sample where all tested ranges for all variables are included. The second regression restricts parameter values to those found to exist in past studies. The independent variables include the following: Disposition Time is the time it takes to resolve a foreclosed mortgage. Foreclosure Discount is the percentage by which the subject property decreases in price as a direct result of being foreclosed upon. Susceptibility to Normative Influence measures how easily people can have their belief changed as it relates to their willingness to strategically default at various stages of being underwater in the mortgage. Social Connectivity measures how many households are within the social circle of each homeowner. Mavenism represents the ratio of Mavens to total people in the sample.

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Restricted Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unstandardized Beta (Std.Error)</td>
<td>Standardized Beta</td>
</tr>
<tr>
<td>Disposition Time</td>
<td>-0.782** (.005)</td>
<td>-0.492</td>
</tr>
<tr>
<td>Foreclosure Discount</td>
<td>-0.180** (.001)</td>
<td>-0.440</td>
</tr>
<tr>
<td>Susceptibility to</td>
<td>-4.074** (.062)</td>
<td>-0.241</td>
</tr>
<tr>
<td>Normative Influence</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social Connectivity</td>
<td>-3.866** (.145)</td>
<td>-0.090</td>
</tr>
<tr>
<td>Mavenism</td>
<td>-2.401** (.263)</td>
<td>-0.028</td>
</tr>
<tr>
<td>Sample Size</td>
<td>66,377</td>
<td></td>
</tr>
<tr>
<td>F-Statistic</td>
<td>8,582.10**</td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>.000</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-Squared</td>
<td>.393</td>
<td></td>
</tr>
</tbody>
</table>

** Significance at 1%; * Significance at 5%

The popular press defines being underwater as owing more to the lender than the property is worth.

Today, over 16 million homes (28% of all homes) are underwater and another 9 million are dangerously close to becoming underwater in the near future. It is our assertion that historic foreclosure levels consisted almost entirely of economic defaults, whereas a larger, albeit unknown, percentage of defaults today are strategic in nature.

Seiler, Lane, and Harrison (2012) document the impact that Mavens can have on the decision-making of homeowners.

Participation in a housing market and home ownership in a neighborhood are both inherently social activities. Individual beliefs and actions that may influence others (e.g., foreclosure decreasing the value of their neighbor’s homes) are therefore naturally subject to the influence of endogenously generated social norms. As individual circumstances change, violation of social norm may be unavoidable, but as more and more individuals are unable to avoid violation, the norm itself may begin to change.

The disease in our model is the advocacy of strategic default; the treatment is the expressed opposition to strategic default.

Kramer (1996, 2001a, 2001b) used economic concepts to explain epidemiological behavior. For Example, Kramer (1996) used economic theory to explain people’s sexual behavior
surrounding the burgeoning of the AIDS crisis. In contrast to Kramer’s work, we bring an epidemiological solution into a real estate setting.

8 Engelberg and Parsons (2011) examine the Barber and Odean (2000) data which covers the period from 1991-1996. Importantly, this is a period prior to the Internet media boom.

9 Beliefs relating to the acceptance of the idea that it is or is not advisable to strategically default form gradually in individuals based on interactions with everyone, not just media. Belief formation is created over time in a complex environment that includes the person’s economic status as well as the information they receive from a variety of sources.

10 Christie (2012) estimates the negative impact of a mortgage default to be between 85 and 160 point off a FICO score. FICO (2011) reports the number as 150+ points.

11 See Zurada, Levitan, and Guan for a methodological discussion.

12 See MacDonald and Winson-Geideman.

13 Each property is our home is unique, and thus issues found in Zhou and Haurin (2010), Zahirovic-Herbert, and Chatterjee (2011), Winson-Geideman, Jourdan and Gao (2011), Shin, Saginor, and Van Zandt (2011), and Plaut and Plaut (2010) are not at issue.


15 We abstract away from such details as found in Benefield, Pyles, and Gleason (2011), Hohenstatt, Kasbauer, and Schafers (2011), and Seiler, Madhavan, and Liechty (2012).

16 The original Forenet model is a purely economic-based model and is discussed in Gangel, Seiler, and Collins (2012).
When homes get foreclosed upon, they may become vacant, remain occupied by the original owner, become occupied by squatters, and so forth. Because our model uses the results of empirical studies which examine actual foreclosure markets, we implicitly incorporate the exact mixture of occupancy outcomes within our model. Alternatively stated, our model naturally reflects the true housing foreclosure market since our inputs match the outputs from other studies that examine the mortgage markets as they naturally occur.

This value is arbitrary, but reflects a maximum of a 6% change per month from an individual. If the weight of susceptibility was at its maximum (one), the a highly susceptible individual could completely change his belief, from one extreme to the other, within year. We deemed this a reasonable assumption.

In the field of epidemiology, this information is typically shown using Clustering analysis and graphs. For the sake of brevity, these graphs are suppressed here, but are available from the authors upon request.

It is unclear whether there is an undiscovered mathematical relationship that aligns our results with those of Gladwell’s which transcend a multitude of areas, or if it is just a pure coincidence.

Although not reported for the sake of brevity, we confirm our earlier result that bad Mavens (in fact, none of the social network variables) can collapse an otherwise healthy real estate market. This makes perfect sense because no matter how easily influenced to adopt a strategic default philosophy, rational people would still not walk away from a home with equity in it. There is only a financial incentive to walk away when the home is underwater. In prosperous economic times, this tends not to be the case.
HEC studies often struggle with sample selection bias, difficulty in generalizing results due to the lack of consistency across HEC programs, the fact that the majority of the studies pre-date the current housing decline which is unlike past declines in program history, periodic lack of significant results, and difficulty in ruling out alternative explanations.  

HUD reports that in 2010, over 2.1 million Americans received one-on-one counseling from HUD approved sources. Approximately 1.4 million of these people received advice relating specifically to foreclosure prevention.