RESEARCH INSTITUTE FOR HOUSING AMERICA **SPECIAL REPORT**

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STRATEGIC DEFAULT IN THE CONTEXT OF A SOCIAL NETWORK: AN EPIDEMIOLOGICAL APPROACH

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EXECUTIVE SUMMARY

The real estate market is currently experiencing the worst crisis since the Great Depression. Unemployment has caused people to involuntarily default on their mortgages, while falling home prices have encouraged others to voluntarily stop paying their mortgages. While the total number of defaults can be measured with a high degree of precision, whether or not those defaults are due to an *inability* to pay or an *unwillingness* to pay is typically unobservable from market data. Before reaching a strategic default decision, borrowers must consider numerous federal and state-level laws. Each of these laws directly relates to the economic advantages and disadvantages associated with the choice to strategically default. Whether by choice or necessity, as foreclosures increase, they have an increasingly negative impact on the price of the healthy homes around them. One default does little to negatively impact the price of surrounding homes. However, as more and more mortgages in the neighborhood go into default, the negative impact is felt at an increasing rate. Much the same way as a disease spreads throughout a population, so too do decisions to "strategically" default.

In economic terms, a foreclosure has a negative externality. Not only does it lead to losses for the borrower and the lender of the subject property, it also lowers surrounding property values. Past studies have used traditional methodologies to measure the impact of foreclosure contagion on surrounding home prices in terms of both time and distance. The results of such efforts have produced extremely different measures of contagion severity, prompting us to take a different approach. Instead of measuring the contagion effect, we use the wide range of results from past studies as a starting point, and then determine the impact this range will have on the housing market under varying market conditions experienced over time. To accomplish this goal, it is necessary to use an agent-based modeling (ABM) approach. Specifically, we begin by creating a simulated real estate market that reasonably resembles the real world. We are then able to perform a wide range of sensitivity analyses that encompass all values found within the range of extant literature findings.

Based on studies demonstrating that the strategic default decision goes beyond purely economic considerations, we build into the ABM model a social network component to incorporate the burgeoning sentiment that it maybe advisable in some situations, to strategically default on a mortgage obligation. It is becoming increasingly clear 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 consciously (and subconsciously) look to their peers when forming opinions, habits and behaviors. By studying these processes of social interactions quantitatively and modeling these highly interdependent influences, we can achieve a much more complete understanding of decision making, even for seemingly very individual, independent decisions such as the decision to strategically default. Especially throughout the past decade, interdisciplinary attention to social network methods has led to a number of fascinating applications in such areas as sociology, psychology, biology, epidemiology, marketing and economics.

Accordingly, we theorize that the advocacy of strategic default can be likened to a disease, and measure how quickly this disease can spread throughout a society. When modeling disease spread, individual differences in susceptibility to infection must be considered. A recent information cascades study published by Seiler (2011), provides data on people's Susceptibility to Normative Influence (SNI) as they relate to mortgage default behavior. SNI 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.

The rate of disease spread is also a function of the level of contagion in 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 is measured based on data collected in Seiler (2011) which describes a "Maven" as a person who is an expert in real estate. This is a person to whom people turn for advice on difficult or complex real estate decisions. Mavens are more contagious than non-Mavens because people place greater trust in their opinions.

A final variable that is considered is social connectivity. Mavens, who have larger social networks, are better able to spread the disease simply because they come in contact with greater numbers of people. The model shows that real estate experts can greatly impact mortgage markets through their use of behavioral advocacy. In fragile markets, advice by influential Mavens can result in a flood of strategic defaults, causing a contagious downward spiral of home prices and potentially a market collapse.

Overall, disposition time is the most important economic / legal variable on which to focus to prevent a housing market collapse, while 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. Similarly, the finding that SNI is the most significant epidemiological variable is important because policymakers can pursue various techniques to change popular beliefs about whether or not it is acceptable to strategically default.

INTRODUCTION

The current economic crisis followed the collapse of the U.S. housing market.[1] High rates of unemployment have caused many homeowners to (economically) default on their mortgages due to circumstances outside their control. Additionally, falling home prices and the prospect of being underwater[2] for many years to come has caused countless others to voluntarily (strategically) default on their mortgages (Guiso, Sapienza, and Zingales, 2011). While no one knows exactly how to measure when a strategic default, as opposed to an economic default, has occurred, most studies strongly suggest that strategic defaults are on the rise (Guiso, Sapienza, and Zingales, 2011; White 2010; Fannie Mae 2011; and Seiler et al. 2011).

If previously cited studies are correct in suggesting that the strategic default decision goes beyond purely economic considerations, then behavioral models must be constructed to better understand future homeowner decision making with regard to the decision to default on a 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 decision. To model the social aspect[3] of the decision to strategically default, we incorporate a social network component into the agent-based model (ABM) framework created by Gangel, Seiler, and Collins (2011). We theorize that the popular 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 released, 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 a financial perspective, this methodology has never before been adopted. The novelty of our approach to understanding strategic default and its effect on the housing market and overall economy is made possible by merging theories from both economics and epidemiology.

Social network models go beyond 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 markets.[4] Housing pundits, or real estate Mavens, share their expert opinion with a large audience on a frequent basis through such media outlets. These social networks create the potential for much faster disease spread / cure than in the past.[5]

The extent to which 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, a real estate Maven with a nationally syndicated radio or television show has a greater ability to impact societal beliefs than a college professor who is known only to her students and possibly the immediately surrounding community.

While the sender of the signal is important, 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 okay to strategically default on ones mortgage? To capture this variable, we use the strategic default philosophical adoption values in Seiler (2011) and Seiler, Lane, and Harrison (2011) to measure the Susceptibility to Normative Influence (SNI) based on the original theory of Bearden, Netemeyer, and Teel (1989).

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.

We find that the most critical economic / legal variable to avoid a real estate market collapse as it relates to mortgage foreclosure contagion is disposition time — the number of months it takes to transfer a home in default to a new owner. Disposition time has recently increased from its historic level of just three to five months to over several years in some markets across the country. This is disastrous for a housing sector trying to recover from a crisis.

OVERVIEW OF MORTGAGE PERFORMANCE METRICS THROUGH THE CRISIS

Housing is a vital component of the U.S. economy, accounting for nearly as much wealth as the stock market. In 2000, residential real estate represented 33 percent of households' net worth. By 2006, that number had increased to 48 percent. At the same time, mortgage debt divided by GDP increased from 54 percent to 89 percent, clearly indicating that while home values were increasing, so too was their use as "ATM machines." Wealth extraction was on the rise due to a decrease in the cost of tapping equity in the home and lower interest rates.

Price-to-rent ratios, which historically hovered around a stable index of 100 had increased to 155 at the height of the market in 2006. Clearly, this relationship was out of equilibrium. Home price increases have been at least partially attributed to an improved access to mortgage market debt through relaxed lending standards (no doc loans, no down payment loans, option ARMS, etc.), the Fed's keeping interest rates too low for too long, and housing policy that aggressively pushed homeownership rates higher.

At the end of 2005, most macroeconomic data indicated a thriving economy. Home prices were increasing at near double-digit rates per year, unemployment was decreasing and foreclosure rates were hovering around their historic average of just 1 percent (see Exhibit 1). In 2006, however, all indicators began to turn around. The unemployment rate began to increase, home price appreciation rates slowed dramatically and foreclosure rates started to increase. By 2010, foreclosure rates had skyrocketed to over 4.5 percent.

Today, according to CoreLogic data, almost 11 million homes (22 percent of the market) are underwater and another 2.4 million have less than five percent equity. Prior to the current crisis, outside of certain, severe regional downturns (the oil patch in the mid-1980s, California in the late 1980s), strategic default has been relatively unknown in the United States. 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. Studies attempting to measure the difference between the two are discussed below.

Exhibit 1. Historic Mortgage Performance Metrics

Exhibit 1A

National Unemployment Rate, 2001–2011

Exhibit 1B

Seasonally Adjusted House Price Appreciation Rates, Purchase-Only Index

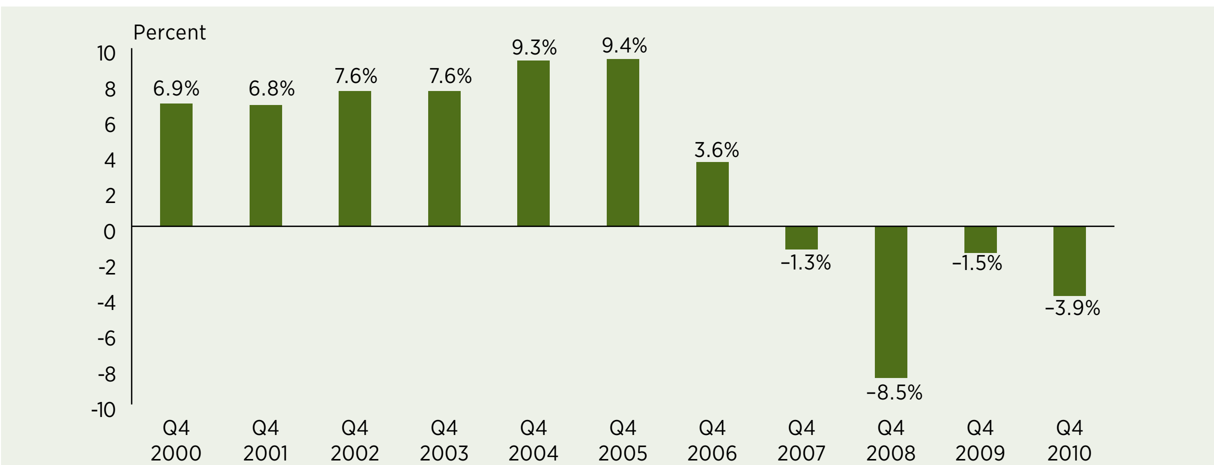
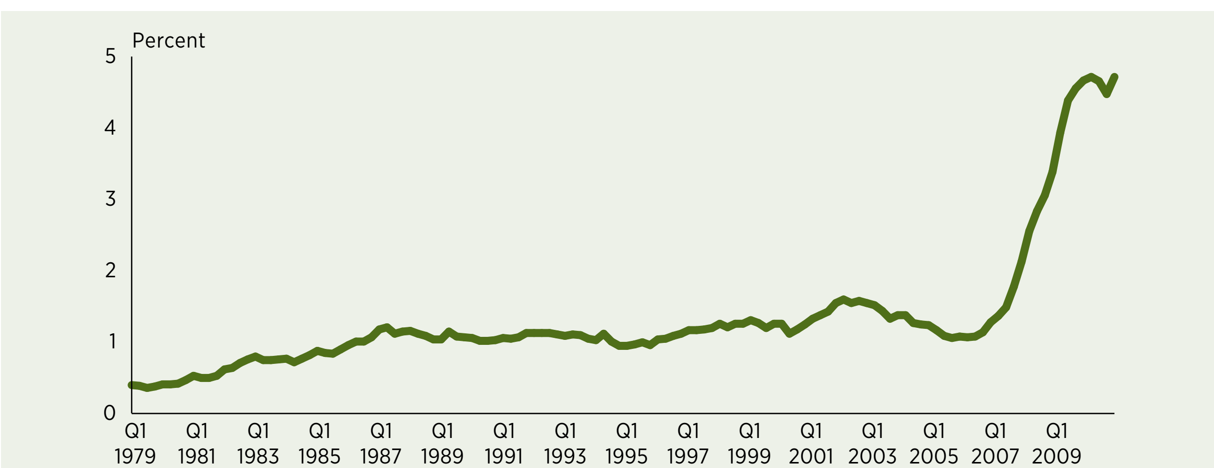


Exhibit 1C

National Foreclosure Rates



Source: Mortgage Bankers Association

OVERVIEW OF MODELS TO PREDICT DEFAULT

How to predict general mortgage default

Conventional wisdom among modelers in industry and academia is that mortgage default can be explained through the use of a dual-trigger model. 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 pocket 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 make up for the negative equity position, including tapping a savings account, borrowing from family / friends, accessing capital through credit cards, etc.

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 the stiff financial consequences of breaching his mortgage contract. Penalties include a severe hit to his credit score,[6] difficulty in obtaining future credit, a higher cost when borrowing money in the future and so forth.

In attempting to predict the drivers of default, most experts would agree that borrower credit score has historically been at the top of the list. Conventional wisdom is that if you want to know how someone will behave in the future, the best predictor is to examine how they have behaved in the past. Credit scores summarize past loan performance of the individual and are useful in screening out poor credit risks.[7]

Equity position in the home is a second measure proven to be successful in predicting defaults. Most studies have historically measured loan-to-value (LTV) ratio at origination[8] and/or current LTV, accounting for amortization of the loan balance and changes to the home value. LaCour-Little (2008) explains that the problem with using LTV at origination is that changes in home value, particularly in this downturn, can quickly erode initial equity in the property. Additionally, if the loan was a refinance, appraised values may not have accurately captured initial equity in the property. Current LTV can be calculated through the amortization calculation and by marking-to-market the property value using the change in a local home price index.

Junior loans are also a contributor to poorer performance as they increase the contemporaneous LTV. From a modeling standpoint, it becomes extremely difficult to capture this effect because often, secondary liens are originated by lenders other than the originator of the first loan. What is then required of researchers is to combine datasets from multiple sources in order to examine the entire financial picture of the borrower. For example, an institution's property-level data would have to be merged with credit reporting agency data to identify all the debt owed by a borrower.

Third-party originators, such as mortgage brokers, have been associated with worse performance on loans. Some argue that mortgage brokers are less concerned with future performance than they are with originating a loan, and as a result, they are willing to place homeowners into mortgage products with required payments that may not be sustainable.

What is difficult about building models to predict default based on past loan performance is that performance on loans not made cannot be measured. Alternatively stated, it stands to reason that an adjustable rate mortgage (ARM) is far riskier than a fixed rate mortgage (FRM), due to payment shocks that occur when interest rates increase. However, if the lender recognizes this risk before making the loan, then he can build certain features into the loan to reduce such risks (or increase the APR on the loan to compensate for it). For example, if the lender wants to reduce the risk on an ARM, he can require a larger down payment (i.e., a lower LTV at origination), apply stricter underwriting standards (i.e., higher credit score, higher income-to-debt ratios and so forth), etc.

Remaining constraints on the accuracy of default models that are often discussed, but difficult to quantify, include the reputational capital of the borrower being negatively influenced by a default, heterogeneous tax treatments resulting from a borrower's default, and the interaction between default and filing for bankruptcy. When it comes to predicting defaults, it is not just the buyer's behavior that models have to understand. Lenders play an important role as well. A buyer determines whether or not he will default on his mortgage. But, a lender then has to decide what action will be taken from there. Will a workout be pursued or possibly a foreclosure? Does the borrower reside in a recourse state where the lender can go after more than just the collateral provided by the home? How much will it cost the lender to pursue deficiency judgments in the case of foreclosures? Is it worth the time and money to pursue deficiency judgments by the lender? Does the answer depend upon the net worth of the borrower? These are all relevant factors to consider when comprehending the feedback loop between buyer decision making and resulting lender actions.

In sum, there has been a vast amount of research performed in the area of residential mortgage default prediction by a number of highly respected academic and industry researchers. At the same time, since 2006, many of the drivers of default have changed, at least in terms of their relative strengths. As such, predicting default remains a constantly moving target. This is why studies like ours are needed to reflect the changing times and evolving philosophies surrounding mortgage default.

How to predict strategic default

Modeling strategic default is somewhat different from modeling economic default. 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 as syndicated radio or television shows, newspaper columns, blogs, or Web sites, 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 possibility to strategically default has certainly been brought to the attention of current homeowners like never before.

While the drivers of economic default are reasonably understood, the drivers of strategic default are less clear. Fannie Mae (2011) and Guiso, Sapienza, and Zingales (2011) identify the incidence of strategic default indirectly by asking people to express whether they know anyone who has done it. Seiler et al. (2011) take the next step by asking people to self-select into the category of strategic default. Presumably, a person's willingness to admit this activity is predicated on their trust in the authors' promise that their anonymity is protected. From a practical standpoint, this sort of self-selection process is not helpful for organizations who seek to specifically identify such individuals, ex-ante. It is only helpful indirectly in that strategic defaulters' motives may be better understood to prevent future strategic defaults from occurring.

Goodstein et al. (2011) are the first to attempt to identify "potential strategic defaulters" using loan-level data in order to discern the ability of homeowners to continue making loan payments. The difficulty with their method is that what is truly needed is month-by-month borrower income and asset figures to match up to the borrower's loan performance data over a long period of time. Even if a bank were to house this information for borrowers, there would still be the problem of having to identify all of the other assets the borrower has elsewhere. Without a complete all-encompassing view of the borrower's portfolio, the analysis will never be definitive.

Even with complete micro-level data, Goodstein et al. (2011) and Seiler et al. (2011) warn that no system can be truly successful at identifying strategic defaulters because of the fuzziness of the decision. Alternatively stated, while the total number of defaults can be measured with a high degree of precision, whether or not those defaults are due to an *inability* to pay or an *unwillingness* to pay is typically unobservable from market data. Even if income level and debt ratios are observed, it is still not possible to infer intent from purely economic data. How does one independently define an inability to make a mortgage payment? Could a borrower take on a second job to keep up with an ARM payment that recently reset to a higher level? Could a non-working spouse from a single-income family find employment to make up for an income shortage? What about the potential to borrow money from a family member or friend or a newfound willingness to tap into a retirement account or a child's education fund? While many of these ideas may seem unpalatable and/or potentially poor economic decisions, they all represent potential sources of funds that could be used to continue making mortgage payments if a borrower really wanted to do so.

Guiso, Sapienza, and Zingales, (2011), White (2010), and Seiler et al. (2011) 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, and of course, being underwater on the mortgage are the drivers that may tip the scales in favor of strategic default.

In sum, it is simply not possible to measure with a high degree of confidence the difference between an economic default and a strategic default. This is precisely our motivation for creating a simulated real estate market where we are able to conduct experiments to estimate the impact of an increase in the willingness to strategically default within a stylized framework. Without running simulations under a variety of hypothetical market conditions, we will be left to speculate on the impact of such borrower actions.

How to identify contagion effects

Mortgage foreclosure contagion is defined as the negative impact that the foreclosure of a single home has on the home prices of surrounding properties. In economic terms, a foreclosure has a negative externality. Not only does it lead to losses for the borrower and the lender of the subject property, it also lowers surrounding property values. 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; and Goodstein et al. 2011). While estimates of the severity of the foreclosure contagion effect vary, it is clear that asset prices in residential real estate markets are heavily linked across both time and distance when negatively impacted by a foreclosure.

Previous research efforts to explore the foreclosure contagion effect within the real estate market use a hedonic regression methodology. Hedonic models decompose complex, incomparable entities into smaller, comparable constituents for analysis. Once decomposed, the constituents are evaluated to determine their contribution to the state of the original entity. In the case of foreclosure contagion, relationships between foreclosures and neighboring property sale prices are explored by decomposing sales prices with two of the constituents being the number and distances of foreclosures within the proximity of the selling property. This approach has been used to identify and quantify relationships between foreclosures and property values from datasets that contain real estate sale prices and foreclosure events (Immergluck and Smith, 2006; Harding, Rosenblatt, and Yao, 2009; Lin, Rosenblatt, and Yao, 2009; and Rogers and Winter, 2009).

The extant literature suggests that the contagion effect of foreclosed properties is a local one. The effect diminishes as a function of both time and distance. A foreclosure event will have a minimal impact on properties that are located significant distances from it and a maximum impact on properties that are neighbors. Likewise, a foreclosure event that occurred in the distant past will have a minimal effect on its neighbors, while a recent foreclosure will have the largest impact. The extent to which this effect occurs varies greatly between studies. Harding, Rosenblatt, and Yao (2009) suggest the contagion effect is significant within approximately 0.9 miles and five years of a foreclosure event. Immergluck and Smith (2006) state their most conservative estimate to be a 0.9 percent discount for every foreclosure within one-eighth of a mile radius of a given property. On the upper end of estimation, Lin, Rosenblatt, and Yao (2009) find that the foreclosure effect is as high as 8.7 percent. On the lower extreme, Rogers and Winter (2009) conclude the contagion effect to be 1 percent or less. Although the literature offers different values for quantifying the contagion effect, all agree the effect is local and that it is a function of both time and distance. Ultimately, we incorporate the upper and lower values found in these existing studies as range limits in the current analysis.

AGENT-BASED MODELING (ABM)

ABM — Theory and Use

ABM is a modeling and simulation technique that allows for the representation of many individual entities and their actions within a system. Once entity-level behaviors and rules are established and executed, macro- or system-level behaviors emerge from the aggregate actions of the agents (North and Macal, 2007). ABM analysis can be considered a bottom-up approach since the lower-level behaviors are understood and implemented to observe the total system behavior. Other analysis techniques, such as systems dynamics, should be considered top-down approaches because they implement equations which represent the total system behavior (Gilbert, 2008).[9]

ABM is ideal for use when the environment to be modeled is not well understood and when the environment is complex. Due to intellectual constraints, researchers are limited in their ability to anticipate unforeseen outcomes that result from complex systems with continuous feedback loops. In this context, ABM has correctly been applied extensively to show emergent behavior in the social sciences. For instance, Schelling (1969) developed an ABM to explore segregation in urban centers; he demonstrates that even minor racial prejudices create massive segregation.

ABM — Model Design

We begin by developing a purely economic model of housing markets, mortgage default behavior and foreclosure contagion in a world without a social network component. Then, in a later section, after reviewing the social network literature, we add to our economic model the corresponding social network variables, and then examine the incremental effect of the social network.

For the purely economic model, while many intricate sub-functions are constructed within the model, only the three main functions are described here. The property agents have three main functions that mimic real-life events: they appraise value, evaluate default and evaluate sale. The appraisal function is directly based on the comparable sales method. It observes recent sales within a set distance from itself to determine its current value. The default function uses the property's current characteristics to determine if the property experiences a default. The sales function uses the property's current characteristics to determine if the property should be listed on the market for sale. The following section will decompose these three functions to provide insight into the dynamics of the model.

Appraisal Value Formulae

For each agent and at each time-step, which represents one month of real-world time, a function executes to generate the current value of the property. This information is needed for several reasons: for input into the default and sales formulae, and to calculate the average property value for the entire real estate market within the model. Although properties in the real world are not formally appraised every month, it could be argued that an owner does an informal appraisal of his property at periodic intervals. For residential real estate, appraisers generally rely on the comparable sales method. Specifically, they find multiple properties with similar features that were recently sold within the vicinity of the subject property (Ling and Archer, 2009). The transaction prices of these similar properties are then used to determine the value of the appraised property.

The properties within the model are assumed to be physically identical except for their location. This assumption simplifies the appraisal function within the model by allowing it to find comparable sales within a specific time frame and distance. In the interests of simplicity, our model uses a weighted average to determine the price.

The model observes the local properties and collects the sales information from the properties that transacted within the maximum distance and time constraints.[10] A weighting function is derived to calculate the appraisal value as follows. Let Δd_i equal the difference between the i^{th} property and some maximum distance constant, d_{max}. Let Δt_i equal the difference between the i^{th} property and some maximum time constraint called t_{max}. Since only properties that are within the maximum time and distance are considered, both Δd_i and Δt_i are strictly positive. Let d_i equal the distance from the i^{th} property and the appraisal property. Let t_i equal time in months since the i^{th} property was sold. Let p_i equal the sales price of the i^{th} property. The following function weights the sales properties that meet the maximum time and distance constraints and then averages their time and distance elements.

$$\Delta d_i = d_{max} - d_i \, , \Delta t_i = t_{max} - t_i$$

$$Appraised\ Value = \sum_{i=1}^{n} p_i \cdot \frac{1}{2} \cdot \left(\frac{\Delta d_i}{\sum_{i=1}^{n} \Delta d_i} + \frac{\Delta t_i}{\sum_{i=1}^{n} \Delta t_i} \right)$$

If no property sales are found within the time and distance constraints, the model will assign the average price of the entire market from the previous month. If there were any recent foreclosures within the local neighborhood, then a property's appraisal value is adversely affected by them. Mathematically, if there are m foreclosed properties within the constrained radius, then the appraisal value is decreased by the following value:

$$Foreclosure\ Contagion\ Effect = \mu \sum_{j=1}^{m} \frac{1}{2}.\left(\Delta d_j + \Delta t_j\right)$$

To clarify, μ measures the contagion effect severity for a single home on the subject property. However, there is also a "negative feedback loop" which causes the effect of the foreclosed home to linger or negatively contribute to the value of the subject property even after the foreclosure has been resold in the marketplace. It's like dropping a stone into a calm body of water. Long after the stone is gone, the ripple still moves across the water's surface. This "legacy" or "hangover" effect causes a formula that is linear to create an emergent behavior which is not linear, as will be seen in the Results section.

Default Formulae

Once an appraisal value has been calculated, the agent then determines whether or not to continue making mortgage payments. This determination is based on a probability likelihood function. For this study, several different factors drive default: financial capacity, loan type and occupant status. Each of these reasons has its own associated effect on the overall probability of default, which is discussed below.

Driver #1: Home Price Decline

Current appraisal value and remaining loan balance are used to calculate the equity ratio.

$$Equity\ Ratio = \frac{Appraised\ Value}{Outstanding\ Loan\ Balance}$$

In our model, having positive equity carries no additional probability of default.[11] An equity ratio less than one indicates the borrower is underwater and therefore has incurred a paper loss on the property. This loss is not realized until the property is sold to another party. However, the amount of equity influences the decision to sell. This logic is explained in the following section. As the equity ratio moves below one, the probability of an owner defaulting, which leads to foreclosure, linearly increases. Let C_{Equity} equal a constant that scales the effect of the equity ratio. Thus, an equity foreclosure is given by the following formula:

$$For\ Equity\ Ratio < 1,$$

$$Equity\ Default\ \ Effect\ = \frac{(1 - Equity\ Ratio) *\ C_{Equity}}{12}$$

$$For\ Equity\ Ratio \geq 1,$$

$$Equity\ Default\ \ Effect = \ 0$$

Driver #2: Payment Shock

Loan type is composed of two mortgage categories: fixed rate mortgages (FRM) and adjustable rate mortgages (ARM). All loans incorporate an interest rate, based on historic values, which is used to calculate a unique amortization table for each property. Monthly payments are determined by the amortization table. FRMs have fixed interest rates, so the monthly payment does not fluctuate over the entire life of the loan. Therefore, it can be assumed that the borrower can afford the monthly payments throughout the life of the loan, barring major catastrophic events — which are addressed later.[12]

ARMs have an initial fixed-rate period at the beginning of the loan during which the interest rate does not change. Once the fixed period has ended, the interest rate changes annually, as determined by external market forces (Ling and Archer, 2009). An associated monthly payment increase is assumed to increase the probability of default. Likewise, a decrease in monthly payment is assumed to lessen the probability of default. For simplicity, we assume there is a linear relationship between changes in monthly payments and default rates.

Let C equal a constant that scales the effect of the probability of payment shock default. Let IC equal the percentage change between the original and the current monthly payment. Thus the probability of a payment shock-related default is given by the following formula:

$$IC = \frac{Current\ Monthly\ Payment}{Fixed\ Period\ Monthly\ Payment}$$

$$Payment\ Shock\ Default\ Effect = \frac{(IC - 1) *\ C}{12}$$

Driver #3: Investor Default

It has been shown that an owner-occupant behaves differently than an owner who is renting out a property as an investment. Specifically, an owner-occupant has to live somewhere. As such, he is much less likely to default on a mortgage even when his home is underwater (Guiso, Sapienza, and Zingales, 2011). The resistance to default is also persistent in the face of an ability to rent at a rate cheaper than owning. By comparison, a real estate investor is more likely to retain an investment property when their renter's payment exceeds the monthly mortgage payment and is more likely to default when the renter's payment is below the monthly mortgage. Since the renter market is not the focus of this research, the following assumption is made to simulate the dynamics of the renter market: rents move more slowly than home values. If the average property value growth has exceeded the expected growth for a 36-month rolling period, then it assumed average rent is sufficiently below monthly mortgage payments for new loan originations, which increases the probability of investment property defaults.[13] Conversely, if the average property value growth has fallen below the expected growth for a 36-month rolling period, then it is assumed that the average monthly rent is above the monthly mortgage payment which decreases the probability of default from a rent-differential (only) standpoint. Let $C_{Investor}$ equal a constant probability that scales the effect of probability of investor default.

$$For\ High\ Market\ Growth, Investor\ Default\ Effect = \frac{C_{Investor}}{12}$$

$$For\ Low\ Market\ Growth, Investor\ Default\ Effect = -\frac{C_{Investor}}{12}$$

Driver #4: Income Shock

An additional probability of default value is included to represent catastrophic events such as job loss, death, divorce, etc., which result in an immediate drop in income and a corresponding inability to make a mortgage payment. Specifically, let $C_{incomeshock}$ equal a constant that represents the probability of a default due to an income shock that results in an inability to maintain payments.

Total Probability of Default

Each effect just described impacts the probability of default depending on the agent, or property type. Each agent is given a classification when created (e.g., an owner-occupant with a FRM) based on historical data.[14] The following table illustrates the four property variants with the default elements that are used to determine the probability of default.

Table 1

Probability of Default

Default Probability Elements	FRM	ARM
Owner-Occupant	Home Price Decline, Income Shock	Home Price Decline, Payment Shock, Income Shock
Renter/Investment	Home Price Decline, Investor, Income Shock	Home Price Decline, Payment Shock, Investor, Income Shock

The probability of default for a given agent is determined by adding the appropriate component to each individual equation. For example, the following equation is the default probability for properties that are investments with ARM loans.

$$P(Default|\ ARM, Investment)$$
$$= \ Home\ Price\ Decline + \ Payment\ \text{Shock} + \ Investor + \ C_{\text{Income Shock}}$$

Sale Formulae

The sales function is executed every month directly after the default function. This function represents buyers and sellers within the market. For a property to sell, it must first be listed by a seller and then purchased by a buyer. This dynamic is complex and is not the focus of our investigation. To simplify the complexity, an assumption is made to represent the listing and purchasing actions as a single event. We determine the percentage of properties listed for sale each month as a function of overall property values. This is consistent with historical data pulled from numerous sub-markets around the country. Genesove and Mayer (2001) find that properties that have been successful investments are more likely to list than properties that are currently underwater.[15] The model sorts the properties by equity and samples a distribution to determine which properties should be solicited to be listed. This method ensures that all properties have an opportunity to sell, but the properties with the largest capital gains have a higher probability of listing.

The final selling price is the appraised value with an additional factor which represents local competition. Property prices decrease as supply rises and increase as supply decreases. During the sales month, the number of listings are observed and compared with the number of listings that are expected to be found within the selling property's local area. If more listings are observed compared to the expected number, then the local market is competitive. Likewise, if fewer listings are found compared to the expected number, then the local market is not competitive. Upon a sale, new starting point data is included for the property in all areas including loan type, down payment, loan amount, buyer type, etc. A linear function is used to represent this phenomenon as shown below. If we let C_{listing} equal a constant that scales the effect of the listing impact, then:

$$Listing\ Impact = 1 + (Expected\ Listings - Observed\ Listings) * C_{listing}$$

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). 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 outcomes that are inaccessible to explanation by methods that failed to include these social effects (Grabowski 2009). By studying these processes of social interactions quantitatively, and modeling these bi-directional and highly interdependent influences, we can achieve a much more complete understanding of decision making, even for seemingly very individual, independent decisions (e.g., risk perception; Scherer and Cho 2003). 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. The first rigorous developments of network characterization in the social sciences can be traced back as far as the 1930s (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) and economics (Sparrowe et al. 2001; Brass et al. 2004), 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 beliefs 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," 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 increasingly used to explain observed behavior in a number of fields. By understanding this behavior, social networks can also hopefully 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.

COMBINING THE ECONOMIC AND SOCIAL NETWORKS INTO A UNIFIED MODEL

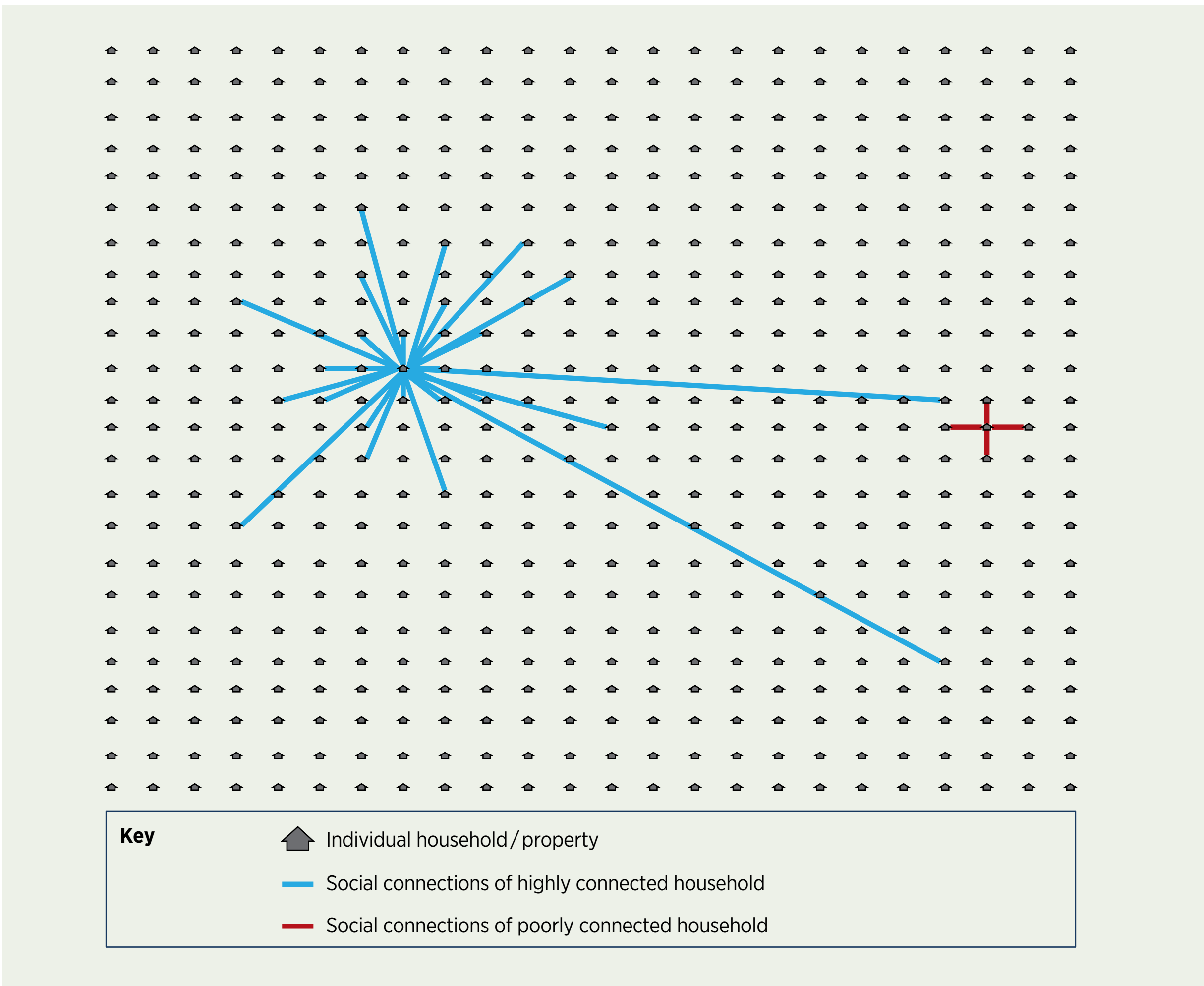
Now that the purely economic model has been created and the social network literature has been reviewed, we next integrate the social network components to measure the differential effects that media and society play in determining pricing behavior in the housing markets. To capture how personal beliefs, especially about socially generated norms, are formed and maintained in this spatial real estate setting, we employ a slightly modified standard network-based model of influence and opinion formation (Friedkin and Johnsen 1990). Details of the model can be found in Appendix 2.

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 (2011). Concerning the social network component of our epidemiological model, the three needed variables are: degree of Mavenism, Susceptibility to Normative Influence (SNI) and degree of social connectivity. The rate of disease spread is a function of the level of contagion in 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. This is a person to whom people turn for advice on difficult or complex real estate decisions. Mavens are more contagious than non-Mavens because people place greater trust in their opinions.

SNI 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 individuals' 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.

Exhibit 2. Graph Depicting Two Households and their Social Connections



Mavenism and social connectivity data was collected experimentally in a separate study as described in Seiler (2011). Mavenism is self-assessed on a seven-point scale, while the social connectivity measure requires 50 names to be randomly selected from a general name directory. Then, the study participant is asked to count the number of people he personally knows (and who knows him) who share a name on this list. The final count reflects social connectivity. SNI is collected in Seiler, Lane, and Harrison (2011) and is measured on a seven-point, self-assessed scale. Since these variables have never been collected elsewhere, we rely on only them to provide what constitutes a reasonable range for the values used in the current model.

Exhibit 3. Screen Captures of Social Network Connections

Exhibit 3A
Overview of the Model's Social Connective Pathways

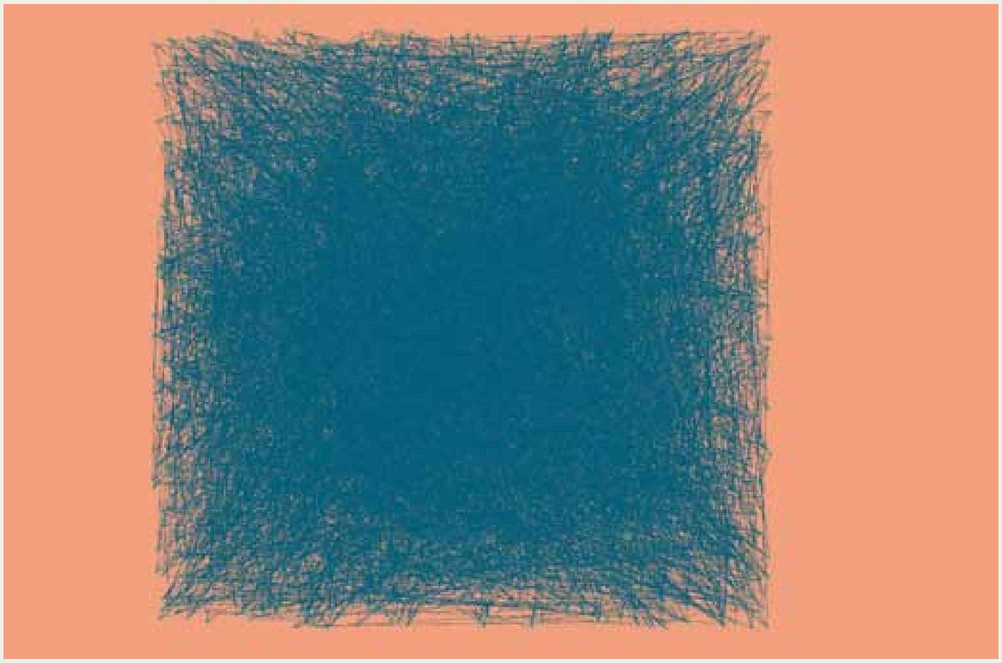
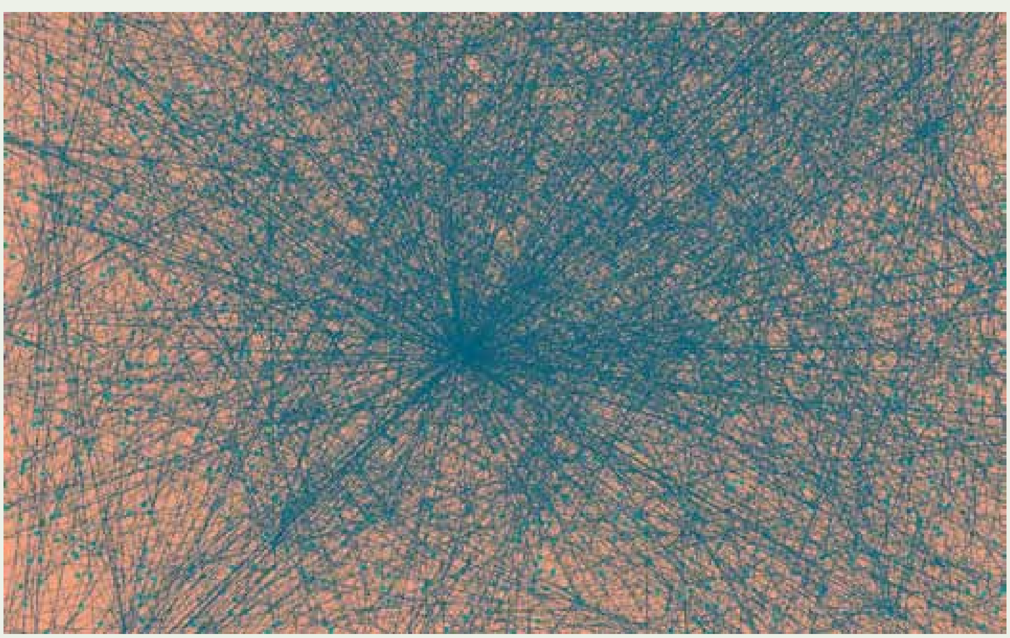


Exhibit 3B
Zoomed in Image of Highly Connected Household



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.

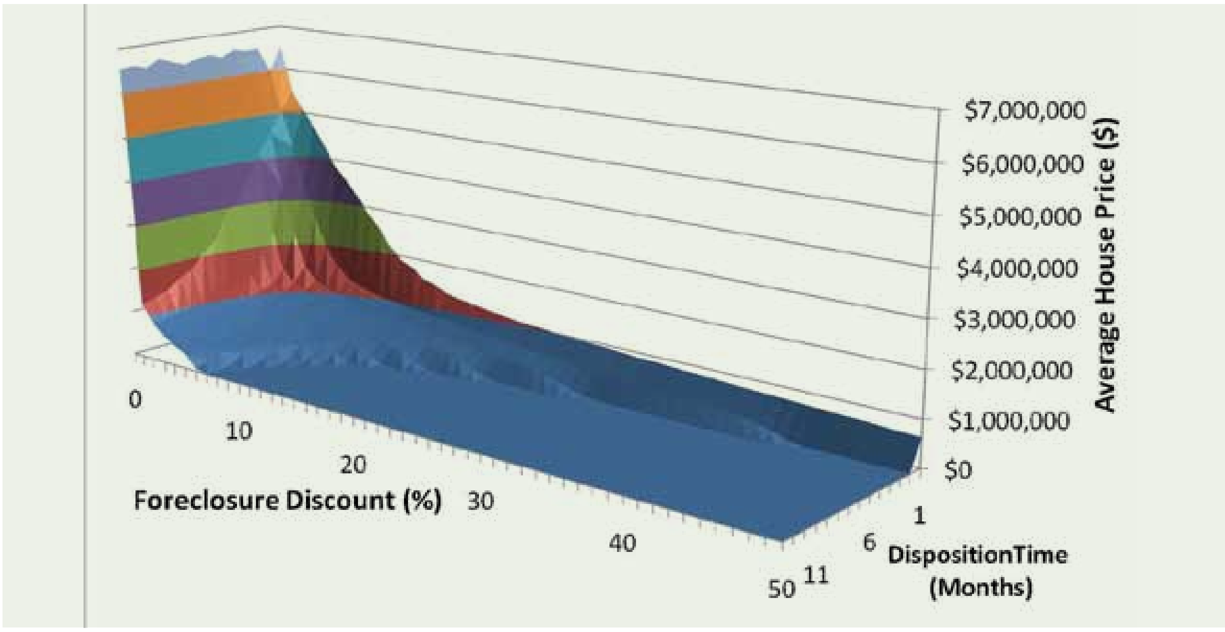
Exhibit 4 reports the results from our economic model of foreclosure contagion without the social network components included. This "lake and mountain" graph demonstrates that, over historically observed foreclosure discount values and disposition times, disposition time has a greater impact on the rate of foreclosure contagion than does foreclosure discount. We next incorporate the social network variables.

The lake and mountain graph can be broken into three key areas. The first is the peak of the mountain. This area represents simulation runs where the ending average property value 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 are lowest. The lake portion of the graph is where foreclosure discount and disposition time are the greatest. The result is a market 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.

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. 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,

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.



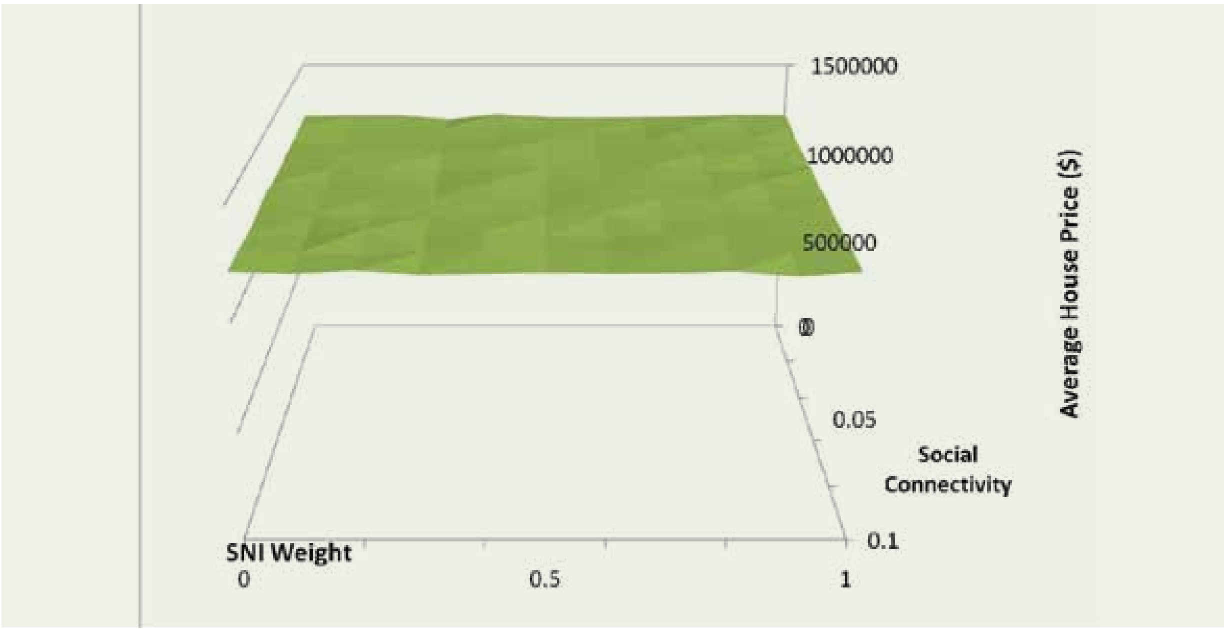
people's degree of SNI and the extensiveness of their social connections do not crash a market. And this is exactly what we expect to be true.

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 how many social network or economic variables are included in 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 you 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

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.



each variable combination and an average of the results was taken. Normally 30 repeats would be considered adequate for the simulation run, but we decided to repeat our simulation runs over 100 times. Even with this excess number of repeat simulations, there is still a large amount of variability within the simulation runs. This "roughness" can be seen in Exhibits 6–9.

Exhibit 6 displays the relationship between SNI and the degree of people's connectivity. The graph is made up of 121 (11 × 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, it is not surprising.

SNI and 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 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.

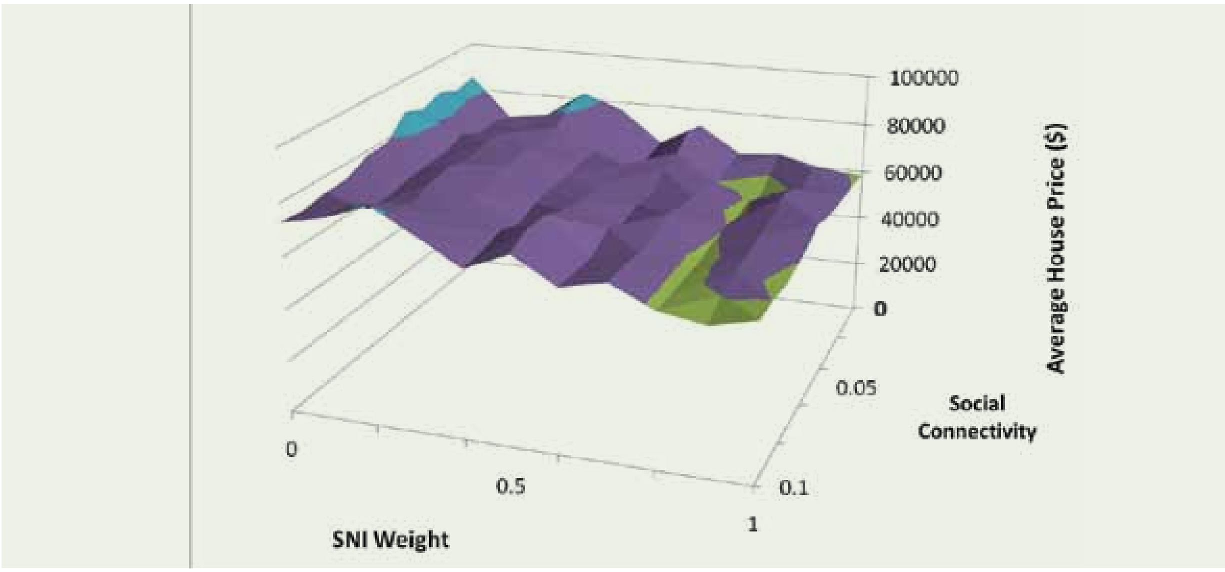


Exhibit 7 performs a similar analysis, but this time SNI is compared with the percentage of the population that is considered Mavens; the graph was made from 13,982 simulation runs. While less definitive, there appears to be more variation in movement from left to right than there is from front to

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.

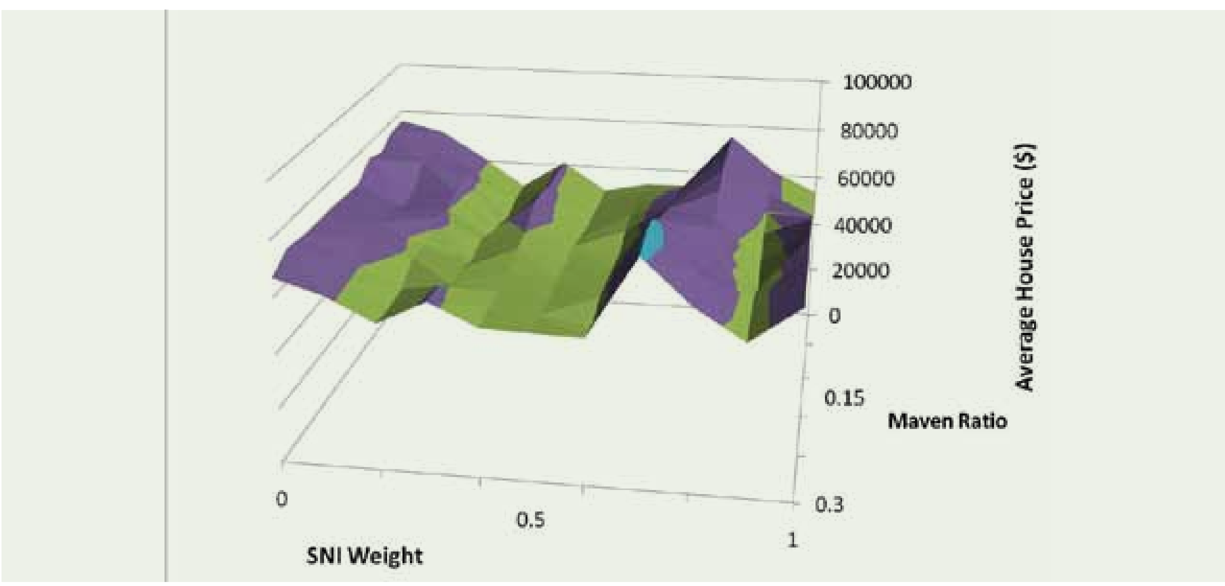
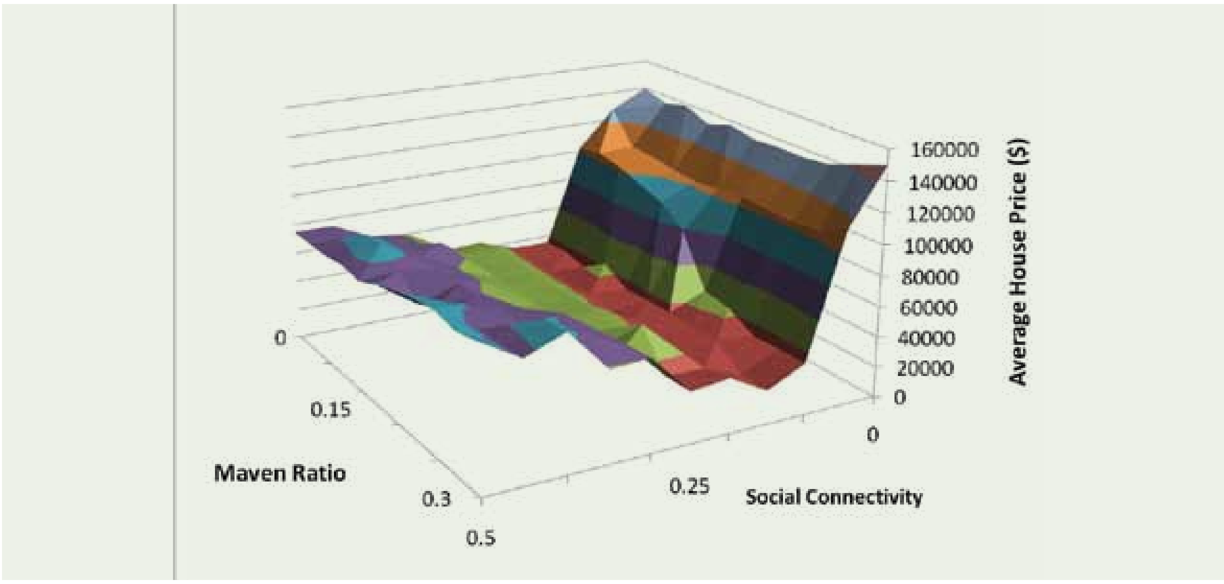


Exhibit 8. Mavenism and Social Connectivity in a Fragile Market

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.



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 a household's social circle is approximately 160. At first glance, it seems odd to expect the relationship to be non-linear, much less to have a defined low point. What is so intriguing about this low point is that, as Gladwell (2002) discusses in his book, there is believed to exist 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. It is unclear whether there is an undiscovered mathematical relationship that drives our results to those of Gladwell's which transcend a multitude of areas, or if it is only a coincidence.

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 by Mavenism. However, just because Mavenism is the third most influential variable does not mean it is unimportant. 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 (2011), Mavenism was measured on a seven-point scale, but no dichotomous delineation was provided to differentiate Mavens from non-Mavens. As such, we use a series of reasonable but arbitrary 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 percent of the people are Mavens.

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.

Exhibit 9A

Bad Mavens in a Fragile Market with Normal Non-Mavens

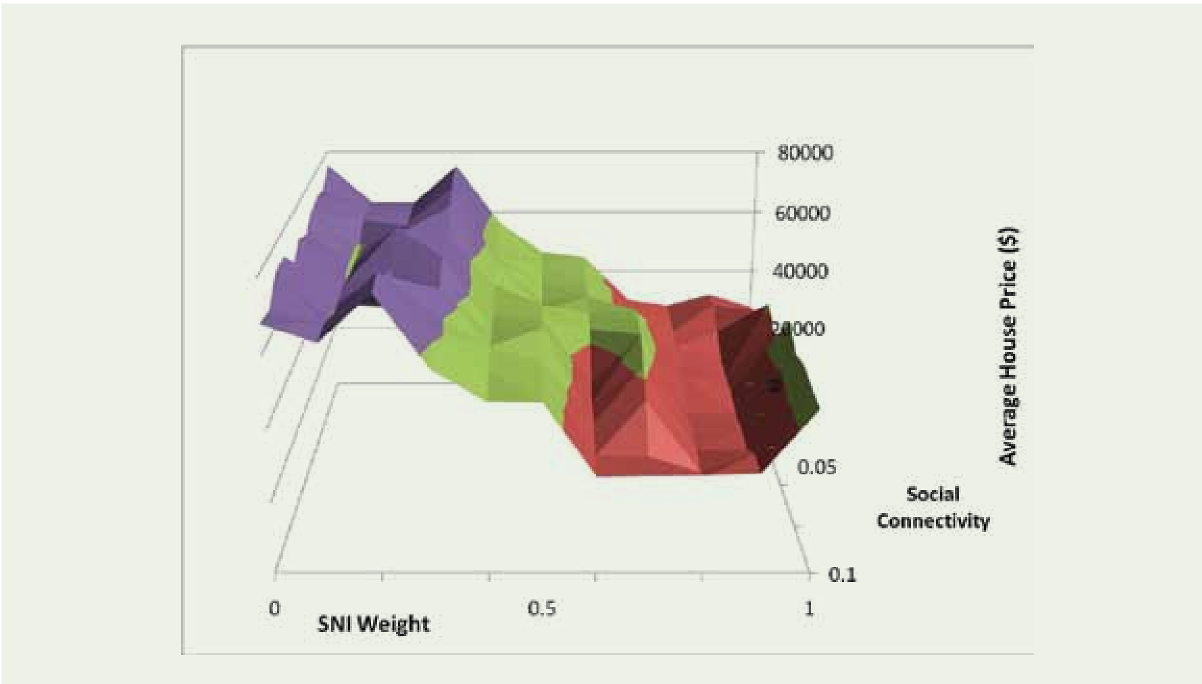
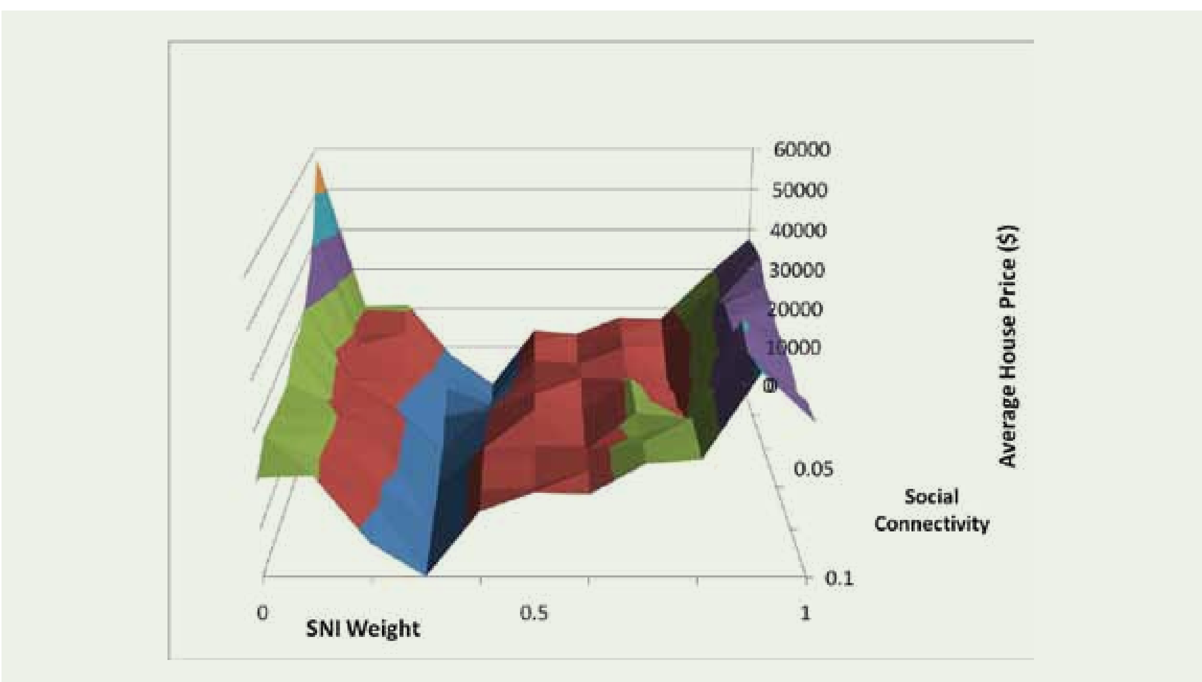


Exhibit 9B

Good Mavens with Bad Non-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.[16]

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 attempt to change public 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 is 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.

Exhibit 10. Regression Results for the Full and Restricted Samples

This table 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 (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. Mavenism represents the ratio of Mavens to total people in the sample.

	Full Sample		Restricted Sample	
	Unstandardized Beta (Std. Error)	Standardized Beta	Unstandardized Beta (Std. Error)	Standardized Beta
Disposition Time	–0.782[a] (.005)	–0.492	–1.392[a] (.015)	–0.398
Foreclosure Discount	–0.180[a] (.001)	–0.440	–1.132[a] (.014)	–0.381
Susceptibility to Normative Influence (SNI)	–4.074[a] (.062)	–0.241	–1.451[a] (.084)	–0.083
Social Connectivity	–3.866[a] (.145)	–0.090	–1.651[a] (.162)	–0.045
Mavenism	–2.401[a] (.263)	–0.028	–1.054[a] (.284)	–0.016
Sample Size	66,377		35,406	
F-Statistic	8,582.10[a]		3,909.61[a]	
p-value	.000		.000	
Adjusted R-Squared	.393		.356	

a. Significance at 1 percent

b. Significance at 5 percent

POLICY IMPLICATIONS AND CONCLUSIONS

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. Similarly, the finding that SNI is the most significant epidemiological variable is important because policymakers can pursue various techniques to change popular beliefs about whether or not it is acceptable to strategically default.

APPENDIX 1. REVIEW OF RECOURSE PROVISIONS IN MORTGAGE CONTRACTS BY STATE

Before reaching a strategic default decision, borrowers must consider numerous federal and state-level laws. Each of these laws directly relates to the economic advantages and disadvantages associated with the choice to strategically default. Below, we walk through a number of these laws and discuss how each impacts the financial incentive for a borrower to walk away from his mortgage.

Bankruptcy Laws

Steinbuks, Desai, and Elliehausen (2010) show there is a high correlation between defaulting on a mortgage and filing for bankruptcy. For this reason, it is important to consider the role bankruptcy laws play in the decision to strategically default. In response to a perceived overuse / abuse of bankruptcy protection laws, the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 made filing for bankruptcy more difficult. In addition to raising the costs of filing by 50 percent (U.S. Government Accountability Office, 2008), the act now requires filers to take credit counseling and debt management classes and provide more detailed income and asset documentation, and removed the filer's choice of whether to pursue Chapter 7 versus Chapter 13 bankruptcy. Under Chapter 7 bankruptcy, the filer is allowed to keep a certain level of assets such as a car, clothing, furniture and so forth, up to state-determined maximum levels. In exchange for these concessions, the individual is allowed to have their unsecured debts discharged. In Chapter 13, the filers must also give up all non-exempt assets, but must repay unsecured debts using future income for up to five years moving forward. While the immediate resolution of Chapter 7 is strongly preferred by filers over the elongated five-year Chapter 13 plan, the new reform has made it substantively more difficult to qualify for Chapter 7 bankruptcy.

Bankruptcy reform and the resulting shift from Chapter 7 to Chapter 13 filings is important to the discussion of strategic default in that Chapter 13 proceedings take much longer to complete. Moreover, because the foreclosure process is halted once a bankruptcy is filed, this action allows for a borrower to stay "rent free" in the home for an even longer period of time. Li, White, and Zhu (2010) explain that in an effort to further artificially extend the free rent benefit to underwater homeowners, Chapter 13 bankruptcy plans can be proposed and then withdrawn several times. Clearly, this action elongates the foreclosure process, thus adding substantial costs to the lender and increasing the incentive to strategically default.

Personal Exemption

Attempting to quantify the level of personal exemption allowance in bankruptcy is a daunting and imperfect art. For example, in Massachusetts, bankruptcy laws provide a protective allowance for "two cows, 12 sheep, two swine and four tons of hay."[17] In Louisiana, the qualitative lists includes "arms, military accoutrements; bedding; dishes, glassware, utensils, silverware (nonsterling); clothing, family portraits, musical instruments; bedroom, living room, and dining room furniture; poultry, one cow, household pets; heating and cooling equipment, refrigerator, freezer, stove, washer and dryer, iron, sewing machine, among other items."[18] Thus, it is difficult, if not impossible, to determine the extent to which these exemptions will be used and valued across state boundaries. As such, we acknowledge that the use of personal exemptions is an imperfect variable. Notwithstanding this objection, we posit that higher levels of personal exemptions benefit those who file for bankruptcy as they allow a person to emerge from bankruptcy with a greater level of assets. Accordingly, higher state-level personal exemptions should result in a greater likelihood of choosing to strategically default.

Homestead Exemption

In bankruptcy, a homestead exemption is the amount of equity in the home that can be retained after completing the bankruptcy process. Seven states currently carry an unlimited homestead exemption provided the person has owned the home for at least 3 1/3 years.[19] Theoretically, higher homestead exemptions benefit borrowers as they keep more home equity after a bankruptcy filing. However, Guiso, Sapienza, and Zingales (2011) find that people typically do not strategically default unless they are substantially underwater. Under this paradigm, a homestead exemption should not be relevant to the strategic default decision, as the borrower typically has non-positive home equity.

Wage Garnishments

In states where garnishing wages is not allowed, debt collectors have a much more difficult time collecting than in states where money is taken directly out of a paycheck before the borrower receives his compensation. Five states substantially restrict, or completely eliminate the ability to garnish wages.[20] Six more states have low garnishment limits of 10–15 percent, while most states allow for wages to be garnished at the rate of 25 percent.[21] The greater the ability of a debt collector to collect payment through direct compensation reduction, the less likely a mortgage holder is to strategically default on his loan.

Real Estate Laws

Real estate laws evolve slowly over time. For example, Pence (2003) explains that statutory right of redemption laws that are in effect today date back to protections put in place back in the 1800s to help farmers who experienced poor crop yields, but wanted to keep their farms.[22] Accordingly, for many of the great plains states, an entire year's protection was put into law to allow for next year's crop intake to make up for the past year's shortage. Real estate laws are also very state-specific.

Recourse

In mortgage default, if the proceeds from selling the home are less than the outstanding balance on the mortgage, it is a called a deficiency. In a recourse state, deficiency judgments may be pursued and, if obtained, become an unsecured claim against the borrower's assets. In a non-recourse state, deficiencies represent deadweight bankruptcy costs which must be borne by the lender.[23] It has been argued that because of superseding bankruptcy laws, recourse loans for many borrowers are defacto non-recourse loans. Specifically, Capone (1996) states that lenders do not follow through on the collection of deficiency judgments because the legal fees usually outweigh the economic benefits. Exceptions to this statement are typically reserved for investor loans and repeat offenders. If a lender's decision to pursue a deficiency judgment is purely economic, then it should be the case that only those with high income and/or high net worth would be pursued. Conversely, for low income and low net worth borrowers, recourse loans should not affect the decision to strategically default. Net worth notwithstanding, a borrower in a recourse state should be far less likely to strategically default on his mortgage knowing that the deficiency can be legally pursued.

Judicial Foreclosure

Foreclosure proceedings across state jurisdictional boundaries can be broadly classified into two categories of events: judicial foreclosure processes and power of sale processes. Judicial foreclosures require formal court action and oversight of the foreclosure process, while power of sale provisions grant a trustee authority to initiate and oversee the foreclosure proceedings, conditional upon borrower default, without formal judicial intervention. An important difference between the two methods is that when a court gets involved, the foreclosure process is both significantly lengthened and substantively more costly.[24] By lengthening the foreclosure process, the homeowner gets to live in the home while not making mortgage payments. This rent-free living represents a potentially significant (carrying) cost to the lender. Accordingly, states requiring judicial foreclosure are hypothesized to support strategic default decisions.

Statutory Right of Redemption

A statutory right of redemption gives the defaulted mortgage holder the opportunity to recapture their property, by a period of up to one year (depending on the state) after the property has been foreclosed upon, provided they catch up on all missed payments (including penalties, interest and late fees). The right to regain possession of the residence remains even after title to the property has been transferred to someone else via a foreclosure sale. On paper, this appears to present an important impediment to the lender when trying to sell the home to a new buyer, as many homebuyers may be extremely reluctant to purchase a property that may be taken back literally months after they have taken possession and moved in. This decreased demand should translate into a lower price received by the lender when the property is re-sold, thus raising the cost of foreclosing to the lender.

In the current study, we are investigating why people strategically default. As previously cited, homeowners who pursue this course of action tend to be substantially underwater at the time they stop making their mortgage payments. Since mortgage defaults often take months to resolve, the missed payments, resulting penalties and late fees continue to create a greater and greater disparity between the value of the home and the amount owed on the home. As the home becomes more and more underwater over time, the economic incentive for a homeowner to exercise their statutory right of redemption becomes less and less. As such, we hypothesize that for the strategic defaulters within our dataset, the statutory right of redemption is of limited practical value.

Where a statutory right of redemption would have value to the borrower is as a bargaining chip early on in the process. Since lenders know the redemption right will increase their foreclosure costs, they should be more willing to work with the borrower before, or at least soon after, default has occurred. However, by the time a strategic defaulter has made the conscious decision to default on his mortgage, negotiating with the lender is unlikely to alter the resulting outcome. Ghent and Kudlyak (2011) provide a summary of real estate laws by state (in Exhibit 11).

Tax Laws Associated with Default

Before 2007, when a lender forgave a portion of the outstanding balance of a loan, the homeowner had to pay taxes on this amount at the ordinary income marginal tax rate. In the wake of the current crisis, there was public outcry to change the treatment based on the following logic: If a homeowner could not pay his mortgage and did not have the assets to make up for the deficiency judgment, he certainly did not have the cash to pay taxes on the amount of the deficiency judgment to the Internal Revenue Service (IRS). Accordingly, the Mortgage Forgiveness Debt Relief Act of 2007 changed the treatment of forgiven debt for owner-occupant homeowners. While there remain several caveats to the various IRS-related rules, the take-away is that in the absence of taxes due on forgiven debt, the financial incentive to strategically default on a mortgage is greater than it was before the rule change.[25]

Exhibit 11. State Foreclosure Laws as Presented in Ghent and Kudlyak (2011)

Property owners may be liable for taxes on the deficiency regardless of whether the loan is recourse or non-recourse. Each state has its own variation on the application of its recourse and deficiency statutes.

State	Judicial or Non-Judicial Foreclosure	Optimum timeline[a] Classification	Recourse	State	Judicial or Non-Judicial Foreclosure	Optimum timeline[a]	Recourse Classification
Alabama	NJ	49–74	Recourse	Nebraska	NJ	121	
Alaska	NJ	108–111	Non-Recourse	Nebraska	J	176	Recourse
Arizona	NJ	115	Non-Recourse	Nevada	NJ	116	Recourse
Arkansas	NJ	90	Recourse	New Hampshire	NJ	75	Recourse
California	NJ	120	Non-Recourse	New Jersey	J	295	Recourse
Colorado	NJ	173	Recourse	New Mexico	J	225	Recourse
Connecticut	J, strict	160	Recourse	New York (NYC)	J	445	
Connecticut	J, by decree of sale	235		New York (Outside NYC)	J	299	Recourse
DC	NJ	48	Recourse	New York (Outside NYC)	NJ	355	
Delaware	J	200–300	Recourse	North Carolina Purchase Mortgages	NJ	120	Non-Recourse
Florida	J	150	Recourse	North Carolina Other Mortgages	NJ	120	Recourse
Georgia	NJ	48	Recourse	North Dakota	J	150	Non-Recourse
Hawaii	NJ	195	Recourse	Ohio	J	217	Recourse
Hawaii	J	320		Oklahoma	NJ	201	Recourse
Idaho	NJ	150	Recourse	Oregon	NJ	160	Non-Recourse
Illinois	J	345	Recourse	Pennsylvania	J	300	Recourse
Indiana	J	266	Recourse	Rhode Island	NJ	74	Recourse

Exhibit 11. State Foreclosure Laws as Presented in Ghent and Kudlyak (2011) (Continued)

Property owners may be liable for taxes on the deficiency regardless of whether the loan is recourse or non-recourse. Each state has its own variation on the application of its recourse and deficiency statutes.

State	Judicial or Non-Judicial Foreclosure	Optimum timeline[a] Classification	Recourse	State	Judicial or Non-Judicial Foreclosure	Optimum timeline[a]	Recourse Classification
Iowa	J	180	Non-Recourse	South Carolina	J	180	Recourse
Kansas	J	230	Recourse	South Dakota	J	340	Recourse
Kentucky	J	198	Recourse	Tennessee	NJ	50–55	Recourse
Louisiana	J, executory process	209	Recourse	Texas	NJ	35–60	Recourse
Louisiana	J, non-executory	269		Texas	J	80–180	
Maine	J	270	Recourse	Utah	NJ	139	Recourse
Maryland	J	46	Recourse	Vermont	J	275	Recourse
Massachusetts	J	75	Recourse	Virginia	NJ	60	Recourse
Michigan	NJ	360[b]	Recourse	Washington	NJ	140–150	Non-Recourse
Minnesota	NJ	270–280[c]	Non-Recourse	West Virginia	NJ	120	Recourse
Missouri	NJ	61–65	Recourse	Wisconsin	J	315	Non-Recourse
Montana	NJ	163	Non-Recourse	Wyoming	NJ	180	Recourse
Mississippi	NJ	90	Recourse				

a. These are optimum timelines from The National Mortgage Servicer's Reference Directory, 21st edition (2004). The optimum timelines assume no delays and are based on uncontested foreclosure actions.

b. The non-judicial foreclosure optimally takes 60 days; however, after that the redemption period begins to run, typically for 6 months. Estimated time for completion for uncontested foreclosure without eviction action is 12 months.

c. The sale in non-judicial foreclosure can generally be held within 90 days; however, there are substantial redemption rights in Minnesota. Thus, including the redemption period the optimum timeframe for non-judicial foreclosure is 270–280 days.

APPENDIX 2. MODEL IMPLEMENTATION DETAILS

After designing the real estate foreclosure contagion environment, simulation runs were conducted using a software package known as Repast Simphony. Repast Simphony is an open-source ABM software developer's kit that is installed in conjunction with Eclipse. Eclipse is an open-source application that is used to build java applications. Another ABM package titled NetLogo was also considered for implementation, but Repast Simphony was selected as the primary tool for this study due to its computing speed and programming flexibility. The model's initial conditions were constructed in a Microsoft Excel spreadsheet for ease of manipulation. Prior to executing the model, Excel writes the initial conditions to a text file which is then read by the model during the initialization phase.

The model consists of 2,500 real estate properties (agents) that are evenly separated in a grid formation.[26] The model reads in the initial conditions which provide the agents with the following information: name, location, loan type, loan age, purchase price, current value, resident type, foreclosure information and listing information. Once the initial conditions have been loaded, the model executes in a discrete time step which equals a period of one month. Each month, the model performs six main functions for each property agent (see Exhibit 12 for a diagram of the steps). First, the model updates loan, foreclosure and listing information on each property, if applicable. Second, the model appraises the value of each property as a function of local sales and foreclosures. Third, the model updates the equity investment property list and computes the average property value. Fourth, the model selects properties to list as a function of the equity list and false reference points. Finally, output for the month is created. This process is repeated over and over again month after month.

Exhibit 13 shows a graphical depiction of a portion of the model's grid and the color of homes that can be found therein. Gray houses are those that are financially healthy; green houses are listed for sale; yellow houses are somewhat underwater; orange houses are substantially underwater; and red houses have been foreclosed upon. Exhibit 14 reveals a series of actual model screen captures, from left to right, associated with a housing market that collapses. In the final screen capture, the entire market consists of red houses which means the market faced an irreversible collapse.

Exhibit 12. Monthly Process of Stepping through the Calculations within the Model

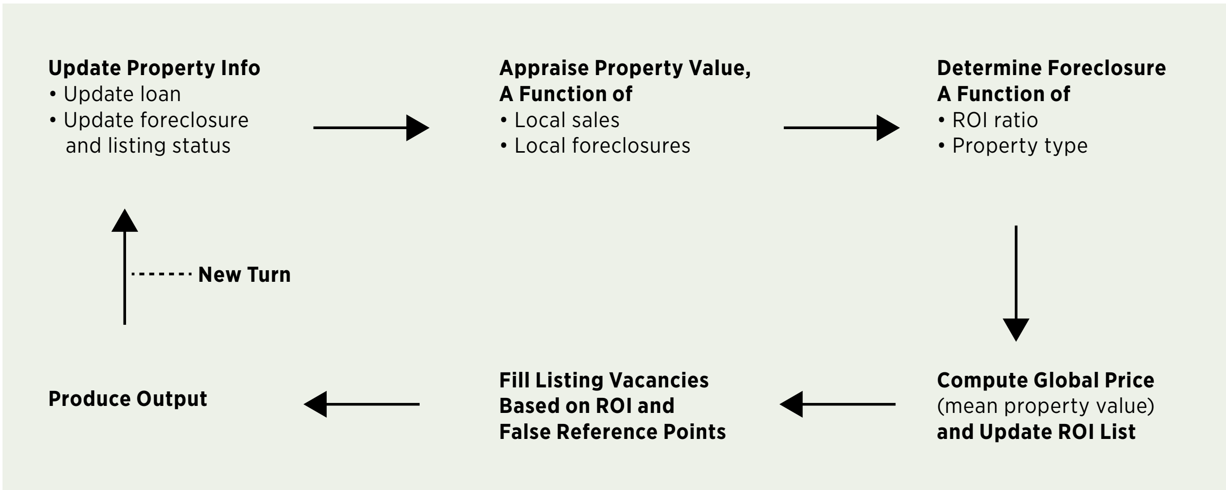


Exhibit 13. Color Coding for Homes within the Model

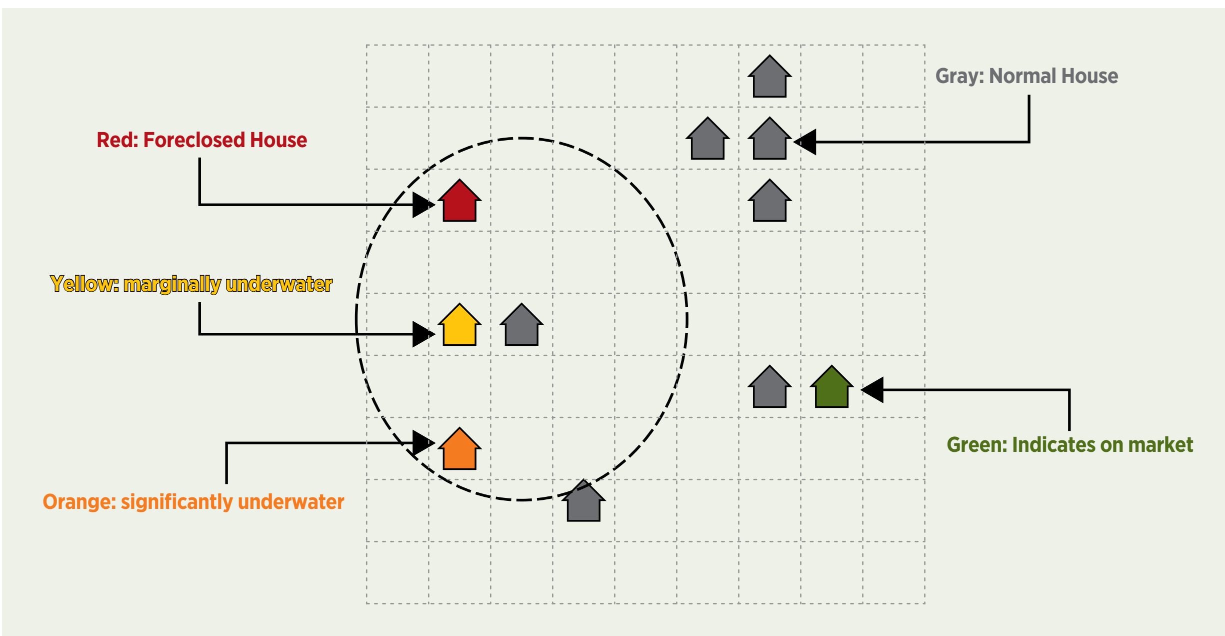
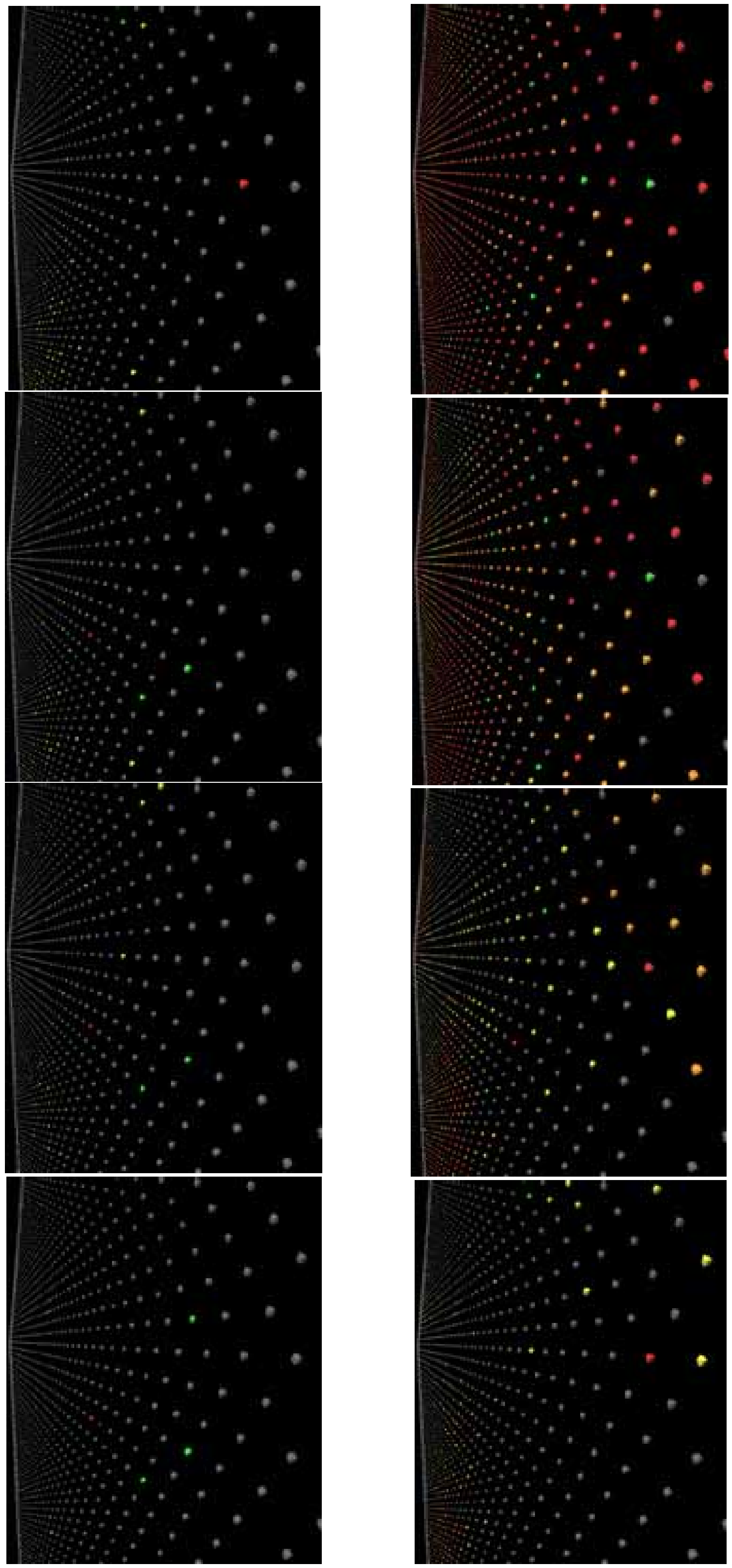


Exhibit 14. Sequential Screen Captures Showing an Eventual Market Collapse Due to Foreclosure Contagion



The mathematical framework for such a model can be defined generally as an iterative process on a set of n individuals who each hold a belief at each point in time. In this basic formulation, at time 1:

$$Y_1 = X_1 B_1 \qquad \text{Equation 1}$$

where, Y_1 is an $n \times 1$ vector of opinions, X_1 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). In subsequent time steps in this model, the opinions of individuals Y_t for $t = 2,3,\ldots$, 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:

$$Y_t = \propto_t W_1 Y_{t-1} + \beta_t X_t B_t \qquad \text{Equation 2}$$

in which Y_t, X_t, B_t and are defined as in (eq. 1), $\propto_t$ is the relative weight of the importance of prior beliefs in the population on shaping current opinions, β_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 tailored the model to investigate our hypothesized influence of socially generated belief regarding strategic default behavior for mortgage loans. How these beliefs translate into actions is then determined by the relationship between belief and external economic factors from the original Forenet model 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 $\propto_t$ term since there is no β_t from a $\beta_t X_t B_t$ term against which the relative value would be judged. 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 that some individuals 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_t 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 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, $y_{n,t}$, which is the n^{th} element of the Y_t vector.)

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 experimentally determined distribution (Seiler 2011, and Seiler, Lane, and Harrison 2011) . We define a distance matrix, Δ, where the distance $\delta_{i,j}$ = the distance from the property held by i to the property held by j in the spatially explicit Forenet model. We then define an intermediate interaction network represented by an $n \times n$ matrix, Θ, where each entry represents $\theta_{i,j}$ the social connection between individual i and individual j (*Note:* therefore $\theta_{i,j} = \theta_{j,i}$, and $\theta_{i,j} = 0$ whenever no connection exists between the individuals). To populate the values of this matrix Θ, we define a neighborhood within a spatial radius, r, and $\forall j | \delta_{i,j} < r,\ \theta_{i,j} = 1$.

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 Ψ_i, which determines the probability of interactions with individuals outside of the immediate neighborhood such that, for each i, $P_i = \{p_1 \quad \cdots \quad p_{\frac{\Psi_i}{2n}}\}$ individuals are chosen at random among the population outside radius r, and for those individuals we set $\theta_{i,x} = 1$. The distribution of Ψ_i for the population is informed by Seiler (2011). Lastly, to explore the impact of inclusion of the influence of acknowledged experts, the top 12 percent of most influential individuals from the data set were chosen to be Mavens.

In each time, t, each individual, i, evaluates his property value, 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 current value of his belief $b_{i,t}$, and updates his belief as defined above. Thus an individual with a belief of one will always default if underwater. Once an individual, k, sells or has his property foreclosed, he is "replaced" in the network with a new buyer.

Based on these definitions and equations (summarized below), the model 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.

- n The number of individuals
- t Time
- Y_t The $n \times 1$ vector of beliefs held by the n individuals in the population at time t. The beliefs are normalized between [0, 1].
- Δ An $n \times n$ matrix with elements $\delta_{i,j}$
- $\delta_{i,j}$ The distance in the spatially explicit Forenet Model between the property owned by individual i and that owned by individual j

- Θ An $n \times n$ matrix with elements $\theta_{i,j}$
- $\theta_{i,j}$ A Boolean matrix representing the existence of social connection between individual i and individual j
- r The spatial radius around an individual's property within which we assume social connection due to neighborhood / proximity
- Ψ_i A relative measure of social connectivity for each individual i
- X_i The set of individuals outside the immediate spatial neighborhood to which individual i is connected in a social network
- M The set of individuals within the social network who exert influence over his peers
- μ_i The relative influence of individual i over peers in the social network. This value is normalized to [0, 1]
- h The relative importance of the previous beliefs of others in the network on individual i's current belief, as opposed to the importance of individual i's own previous belief (for purposes of our analysis, $h = 0.06$)
- S The Susceptibility to Normative Influence (SNI) weight. This range belongs to [0, 1,]
- s_i The Susceptibility to Normative Influence (SNI) for each individual i

The beliefs of all individuals over time are then defined as:

$$y_{i,t+1} = (1 - h * S * s_i)y_{i,t} + h * S * s_i \sum\nolimits_{\forall j \neq i} \left(\frac{\mu_i \theta_{i,j} y_{i,t}}{\delta_{i,j}} * \frac{1}{\sum_{\forall j \neq i} \mu_i \theta_{i,j} / \delta_{i,j}} \right) \qquad \text{Equation 3}$$

Where h is the relative importance of the previous beliefs of others relative to one's own prior beliefs, 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 2011; and Seiler, Lane, and Harrison 2011). In the language of the general model, this equation populates the matrix W_t such that the diagonal entries are equal to $(1 - h)$, and the off-diagonal entries are set equal to $h * S * s_i \sum_{\forall j \neq i} \left(\frac{\mu_i \theta_{i,j}}{\delta_{i,j}} * \frac{1}{\sum_{\forall j \neq i} \mu_i \theta_{i,j} / \delta_{i,j}} \right)$. The appendix provides a discussion of how the model is implemented.

END NOTES

1. See Gorton (2009) and Brunnermeier (2009).
2. The popular press defines being “underwater” as owing more to the lender than the property is worth.
3. 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.
4. 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.
5. Beliefs relating to the acceptance of the idea that it is or is not OK 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 he receives from a variety of sources.
6. Christie (2010) estimates the negative impact of a mortgage default to be between 85 and 160 points off a FICO score.
7. As a word of caution, Wyman (2010) reports that strategic defaulters tend to be people with top credit scores leading up to default. For this reason, credit score may no longer be the best metric to predict mortgage defaults.
8. This metric is commonly alternatively described as the down payment required when buying a home.
9. Systems dynamics techniques are applicable when the system behavior is already fully understood.
10. We specify a 10-house radius sweep for sales within the last six months.
11. To clarify, homeowners can default on a mortgage with positive equity due to a number of reasons which are captured through our fourth component described on page 25.
12. Alternatively stated, in the absence of income shocks such as job loss, divorce, death, etc., the tilt effect would support our contention that an affordable monthly payment today should be more affordable as time passes.
13. This statement only applies to the partial effect of rental income versus mortgage payment differentials on new loans. Clearly, the positive effect of increasing property values will outweigh the economic pressure to default due to negative cash flow differentials.

14. The percentage of FRM versus ARMs, the number of owner-occupants versus investors, etc., are stochastic in that they are drawn from a Bernoulli distribution over time whenever a home is purchased and a new owner is assigned.

15. Bokhari and Geltner (2011) replicate this study using commercial real estate data and support the notion that this behavior may be generalizable across asset classes.

16. 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.

17. www.legalconsumer.com/bankruptcy/laws/#Massachusetts

18. www.legalconsumer.com/bankruptcy/laws/#Louisiana

19. The Bankruptcy Reform Act of 2005 placed a cap on the homestead exemption at $125,000 for those states that had higher levels for anyone who owned the home for fewer than 3 1/3 years.

20. No to extremely limited garnishment states include FL, NC, PA, SC and TX.

21. Low garnishment states include DE, IL, MO, NE, NJ and NY.

22. Capone (1996) shares that the underlying concept dates back even further to ancient Hebrew times.

23. While the direct costs of such an inability to pursue deficiency judgments are borne by lenders, in a rational, competitive, economic marketplace borrowers may share these costs in the form of higher loan qualification standards or more restrictive loan terms and covenants. See, for example, Pence (2006).

24. Wood (1997) finds that judicial foreclosures add 148 days to the foreclosure process, while Jankowski (1999) concludes foreclosure times can be extended by up to 300 more days. Clauretie (1987), Clauretie (1989), Clauretie and Herzog (1990), and Pence (2003 and 2006) all provide further evidence on the economic importance of state-level foreclosure laws and processes to mortgage market outcomes.

25. To learn more about the tax treatment of mortgage deficiencies, please see IRS.gov, specifically, Publication 4681.

26. Although technically the property grid must have physical boundaries such as edges and corners, the mathematics we perform implicitly assume a toroidal or spherical space. Simply stated, the space is treated as being continuous and without boundaries. That is, a home located in the “corner” of our grid shares the exact same mathematical underlying drivers (and neighbors) as a property located exactly in the middle of the housing grid.

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