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Application of Agent-Based Modeling: Simulating Financial Systemic Risk and Contagion within Housing and Financial Markets

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Faizan Khan as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in Political Science with areas of specialty in Computational Analytics and Political Economy of Development.

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Abstract

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By
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Claremont Graduate University: 2019

This dissertation presents an agent-based model (ABM) to model systemic risk in the housing and financial markets from 1986 to 2017 and provides a unique approach to simulating the financial market along with demonstrating the phenomenon of emergence resulting from the interconnected-behavior of consumers, banks and the Federal Reserve. Consumers can buy or rent properties, and these agents own characteristics such as income and may be employed or unemployed. Banks own balance sheets to monitor their assets and liabilities and participate in the interbank lending market with one another. This tool can model the complexities within the United States' housing market, conduct stress tests as interest rates fluctuate, and explore characteristics from the landmark financial crisis and epidemic of foreclosures. The blend of available financial products to consumers (i.e., ARM versus Fixed-Rate) certainly influences demand to purchase properties given that ARM products are more affordable than fixed-rate products; however, these specific products may increase the risk of "underwater" mortgages. The market value of a property is heavily influenced by the value of a neighboring property; therefore, individuals are able to gauge the probable value of a property that has not been developed yet. The blend of available financial products to consumers (i.e., ARM versus Fixed-Rate) certainly influences demand within the housing market given that ARM products are more affordable than fixed-rate products. Overall, these concepts are important as the understanding of the impact from increases in foreclosed properties, changes in rates, available financial products, and more can help policymakers and financial institutions understand and model the non-linear complexities within the housing market.

Dedication

This dissertation is dedicated to my parents, Ahmed and Shahida Khan, for their sacrifices, endless support and love. My mother and father taught me the value of education and a strong work ethic.

Acknowledgements

This work would not have been possible without the immense support and training I received from the inspiring faculty at Claremont Graduate University. I am grateful to each of the members of my Dissertation committee for encouraging and challenging me over the last few years. Dr. Mark Abdollahian, the Chair of this Committee, taught me how to apply analytical techniques to respond precisely to questions about the global political economy. Through his encouragement, I chose to pursue a PhD after receiving my M.S. degree, and it is through his example that I am inspired to apply my skills in the real world. Dr. Zining Yang showed me the importance of leaving the classroom and presenting my work both here and abroad. She mentored me throughout this program and was always willing to brainstorm new ideas for academic papers with me. Dr. Yi Feng taught me the fundamentals of global political economy and fostered my passion for research in such topics as income inequality, trade, investments, and central bank independence.

I will forever be grateful for my family. My mother and father have showered me with so much love and support. Thank you for all that you have done and the sacrifices you have made to ensure your children had the opportunities you did not. Each of my sisters are an extension of my mother, and they took care of and raised me throughout their adolescent years. Nida, Saba, and Sana have always been role models for my brother, Zaman, and me. I am thankful for your never-ending support. Zaman has always been there to listen and ensure that I am making time to relax and enjoy life outside of my professional and academic life. He will forever be my best friend. I wish to thank my two brothers-in-law, Farhan and Saad, for their guidance as the older brothers I needed as a child. Most importantly, I wish to thank my nephews and niece who

constantly amaze me every day. I am excited to see all of the wonderful things you will do in your lives, and I am confident that you will each contribute to this world with your ideas and skills.

I am also grateful for my friends and colleagues who constantly demonstrated their support by being there for me at all times. Jay Chary, Ryan Hughes, Logan Holmes, and Mikey O'Donnell encouraged me to pack my bags and move to California for the sole purpose of pursuing a doctoral degree. The four of you believed in me and have always cheered me on in all my endeavors. Jonathan Cham, Spencer Hayles, and Paul Reynolds, my former roommates and close friends, ensured that I had an incredible time throughout this graduate program while I was far from home. Tom Barr for his endless support and helping me settle in New York City – a place I never thought I would end up.

Finally, I would like to acknowledge my past managers. Paul Wolpe, Jay Henniger, and Eric Shaw, thank you for always being understanding and supportive as I worked towards balancing my professional and academic aspirations. Dr. Jon H. Burkman was the first person to discuss pursuing a doctoral degree with me. Dr. Burkman inspired me to go on this five-year journey and told me that a doctoral program would be a challenging but rewarding personal experience. He was absolutely right.

For all those and more who have brought me to where I am today, thank you. This work would not have been possible without your love and support, and I am eternally grateful. I hope to use the knowledge and skills obtained from this program to the best of my ability.

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Introduction

For many Americans, the opportunity to own a home is part of the "American Dream." Home ownership allows individuals to secure an asset that may potentially appreciate in value over time. The Real Estate Crash of 2007, which transitioned into a global financial crisis, is presently the closest event to a modern-day Great Depression. It was initially a banking and securities crisis, which then evolved into an economic crisis. Diminishing house prices influenced some individuals to strategically default on their payments as their mortgage transformed into an underwater mortgage (i.e., unpaid loan balance is greater than market value of property). Others defaulted without choice due to catastrophic events such as becoming unemployed. These defaults inevitably led to foreclosure of properties. The foreclosure "contagion effect" mimics the concept of a virus spreading into an environment from carrying hosts; therefore, as the number of foreclosed properties in a neighborhood increases, the prices of homes surrounding an "infected host(s)" may be negatively impacted. An immense amount of defaults and delinquent payments harmed the income of banks, and these financial institutions struggled to meet debt obligations to other banks. As a result, housing prices depreciated, and interbank lending tightened.

Researchers attempted to understand the housing market crisis by analyzing various potential determinants such as: monetary policy implemented by the Federal Reserve, the role of sub-prime mortgages and mortgage-backed securities (MBS), lending standards by the financial services sector, and the list continues; however, there is not a consensus as to what truly caused the U.S. to tumble into this detrimental position. What if it was a "perfect storm" including everything listed above plus more? Both, the housing market and financial crisis, are prime examples of complexity. Complex in the sense that there were several underlying factors that contributed to the bubble and crisis. Although these factors may seem like dozens of mismatched puzzle pieces, they are quite interconnected.

The purpose of this dissertation is to describe and demonstrate a simulation tool, which may be helpful for modeling historical, present, and future phenomena related to concepts such as the foreclosure contagion effect between properties, risk mitigation and management of financial balance sheets, and the impact political economic shocks have on the economy. This model allows us to understand and replicate the behavior of consumers and financial institutions and analyze the impact to the environment from changes in interest rates set by central banks. More specifically, this agent-based model simulates and measures systemic risk within the U.S. housing and interbank markets—a complex adaptive system. After the model initializes, I perform stress tests and sensitivity analyses to assess a variety of outputs given specific inputs such as interest rate fluctuations, contagion, etc. These stress tests also demonstrate the feedback effects within the complex adaptive system. The primary contribution of this model, compared to prior literature, is that it combines elements and expands on the models mentioned in the "Literature Review" chapter of the dissertation.

Furthermore, prior models solely isolated certain breeds of agents and their behaviors (e.g., banks or consumers). The model being presented emphasizes and includes the interconnected behaviors and relationships between consumers, banks, and regulatory institutions such as the Federal Reserve. Prior studies typically only incorporated property or consumers as agents (e.g., foreclosure literature), or only banks (e.g., interbank networks); however, I argue that including these various components and agents is important. For example, if consumers are likely to enter a foreclosure, this has an impact on an individual bank's balance sheet. Another example may involve understanding how interest rates influence the demand for varying types of mortgage products to purchase a home.

Regarding the consumer-related results of the simulations, I find that clusters of foreclosed homes have a severe negative impact on neighboring homes. As homes enter foreclosure, this negatively affects a bank's balance sheet as well. In addition, monetary policy and control of interest rates by the Federal Reserve play a critical role in the probability of an interest rate foreclosure. With respect to the interbank network results of the simulations, I run various comparative static experiments and elaborate on the results.

Moreover, this paper is organized as follows: Chapter 2 will be a review of prior literatures, Chapter 3 describes the methodology and research design, Chapter 4 analyzes results from the ABM, and Chapter 5 provides concluding remarks and improvements for future research.

Chapter 2: Literature and Methodology Review

This section will provide an overview of a few core topics that each contribute to the development of the agent-based model presented in this dissertation. The first portion of this section focuses on comparing agent-based modeling with standard linear methodologies (e.g., OLS regression). It will summarize the current generation of methodologies used by financial institutions (e.g., banks) and supervisors (e.g., the Fed) for understanding threats to financial stability (stress-testing and portfolio value at risk). Furthermore, this will explain why and how agent-based modeling can be a powerful non-traditional approach for stress-testing and analyzing value at risk.

Additionally, I will review the various claims by researchers as to why and how the housing bubble occurred. This review will also mention literature that discusses the mechanics of the real estate market as a major component of the financial system. I would also like to briefly address that the consumer-related aspects of the model presented in this paper were substantially enhanced from a Level 1 Axtell-Epstein (1994) agent-based model developed by a group of researchers at George Mason University (GMU) (McMahon, Berea, Osman 2009). In addition, this paper focuses on similar methodologies implemented by Gangel et al. (2013a) to represent the contagion effect and contributes to real estate, foreclosure, and financial literature. Regarding the interbank network aspects of the model, I attempt to replicate scenarios and experiments conducted by researchers such as Nier et al. (2007).

Comparing Agent-Based Modeling and Linear Methodologies

Traditional econometric modeling stems from mathematics to solve for equilibrium. Agent-based models are bottom-up computational models that use simple assumptions to simulate individual agent goals and interactive behaviors over time whereas system dynamics is a top-down approach due to the focus on total system behavior (Gilbert, 2008). Agents can interact with each other and their environment; therefore, changes in other agents or the environment can lead to adjustments in an individual agent's behavior. Ultimately, the combination of rules and interactions contributes to the phenomenon of "emergence." Researchers are able to run experiments using an agent-based model to analyze volumes of data based on the agent interactions in a specified environment (Gilbert, 2007; North and Macal, 2007). Several researchers have used this approach to simulate complex real-world problems. Schelling (1971) used the ABM approach to simulate racial segregation within housing in the United States. Abdollahian et al. (2013a) used ABM to simulate the Human Development theory and analyze the effects from interactions between economics, culture, society, and politics. Abdollahian et al. (2013b) also utilized ABM to model SemPro, which simulates how competing interests and barriers impact siting outcomes and policy for sustainable energy infrastructure. Goldstein (2017) developed a series of ABMs to simulate the housing market in the Washington DC Metropolitan Statistical Area from 1997-2009. As

Haldane (2016) from Bank of England pointed out in 2016, more and more scholars start to use ABM to study economic, fiscal and monetary policies, leveraging the model's capability in studying crisis (Dosi et al., 2015; Geanakoplos et al., 2012).

As mentioned, the housing market is a complex and nonlinear system with a high-level of heterogeneity. Agents in the housing market are heterogeneous due to preferences, income, risk appetite, etc. A linear model would only provide us with limited insight given that there are numerous factors constantly changing within the volatile market. According to Goldstein (p. 10, 2017), "Housing market interactions are more complex than many other markets due to search costs coupled with nonzero costs for waiting, large product differentiation, and the frequent inclusion of mortgage financing." ABMs have the capacity to handle such complexities compared to a traditional linear model. The simulation technique allows us to explore variables and relationships, which are typically difficult to analyze and predict by only using actual historical data. Using ABM, we are able to adjust various parameters to further understand a variable's impact on the simulated environment.

Moreover, it is important to address the cons of using agent-based modeling as a methodological approach. This approach is extremely sensitive to assumptions, since ABMs are ad hoc models. Developers can build any type of model, which will generate volumes of data based on the value and construct of specific parameters and inputs. To assure that a model is valid and robust, modelers should back-test their models using empirical data.

Current Methods for Risk Management: Stress-Testing and Value-at-Risk (VaR)

Financial institutions and supervisors devote much of their resources towards developing and understanding different types of risk within the financial system. Two popular approaches currently used to assess and measure risk include: (1) Value-at-Risk (VaR) models and (2) stress testing. Value-at-Risk is a metric that determines the amount of potential loss in a portfolio and the probability of such event occurring over a specific time period. After the 2008 financial crisis, several domestic and international regulations were implemented requiring the financial industry to report their capital adequacy and perform stress tests pertaining to scenarios such as a bankruptcy, recession, or crisis. The ultimate goal is to assess if a bank possesses enough capital to withstand the consequences of such harmful economic scenarios. Stress testing is a regulatory requirement for banks typically with more than $50 billion assets under management or more per the 2010 Dodd-Frank Act; therefore, these financial institutions are investing resources to ensure they meet regulatory requirements and have a concrete understanding of internal and external risk factors.

Bookstaber (2012) emphasizes that weaknesses exist within the current generation of models as they are, "…unable to model financial vulnerabilities, the shocks that might expose these vulnerabilities, and the process by which such shocks might propagate through the financial system." Additionally, the author discusses the benefits of ABM and claims that it is a promising approach as it is flexible and allows us to specify the non-linearities, complexities, and instabilities within the world we live in. Bookstaber highlights that currently VaR and stress testing rely heavily on historical distributions and events. Thus, these techniques do not incorporate unanticipated shocks and the changes in economic relationships during stressful events, which are not necessarily guided by the past.

Background on the Real Estate Market

Many researchers have analyzed the housing market under different circumstances. For example, scholars have contributed to literature revolving around the foreclosure of properties (Khan and Yang, 2018; Vernon-Bido et al., 2017; Seiler et al., 2013; Gangel et al., 2013a, 2013b, Colins et al., 2013). With respect to the underwater mortgage literature, Archer and Smith (2010), underwater mortgages—loans with balances higher than the actual market- value of the property—were a significant driver for default of payment. Goldstein (2017) developed a series of ABMs to simulate the housing market in the Washing- ton DC Metropolitian Statistical Area from 1997–2009. The author demonstrates that leverage (loan to value ratio or LTV) and expectations primarily contributed to the local bubble along with interest rates, income towards housing, and seller behavior. Goldstein claims that lending standards and refinance rules did not particularly influence the bubble; however, I will attempt to model these factors over time to assess whether they play significant roles in the nation's housing market.

The financial sector, specifically banks, control the supply of loans in the market. Lenders typically do not hold onto mortgages and have the option to bundle volumes of these products together. After mortgages are bundled into a single product, they are sold to various investors. These products are titled residential mortgage-backed securities (RMBS or MBS). A pair of researchers developed a hypothesis to assess the action by banks to created MBS products for investors called "originate to distribute" (Bord and Santos, 2012). In other words, the more loans a bank can originate, the more securitized products such as MBS they can sell to investors.

Additionally, small and mid-sized banks attempted to mimic business strategies similar to large banks. Before the crisis, large banks had insurmountable MBS portfolios. How were small and mid-sized banks going to catch up with large banks? These banks evolved into mortgage originating machines, since this was a powerful strategy to generate high-revenue and remain competitive. During this time, a few factors were in place: (1) interest rates were at an all-time low—which was key for Adjustable Rate Mortgages, or ARMs, because interest rates were fixed for a certain amount of time (typically 5–10 years), and then home-owners would sell the property just before the teaser-rate expired to make a profit and avoid and adjustable rate, (2) Americans wanted to lock down low-interest mortgages and homes as soon as possible to retain affordable payments, (3) lending standards were loose, which may be correlated with originating to distribute (Mian and Sufi 2009); however, Gorton (2008) suggests securitizing mortgages did not lead to these standards and instead loose standards became problematic for the securitization process. Essentially, once the initial fixed rate (also known as teaser rate) for an adjustable-rate mortgage expired, borrowers began defaulting on payments because they were too high while house prices did not appreciate.

As mentioned earlier, researchers have asserted that sub-prime mortgage borrowers, or high-risk borrowers with low credit scores, played a critical role in contributing to the housing bubble because with an increase in demand led to an increase in prices (Mian and Sufi 2009). Given the three factors previously listed, sub-prime mortgages were an easy solution for small and mid-sized banks to generate high volumes. The financial sector could also innovate trading mechanisms for these products (i.e., credit default swaps), which contributed to the bubble and crash (Duca et al. 2011). Banks no longer had to be concerned with risk, since investors were only focused on the pricing of securities and not how loans were originated. Ashcraft and Schuerman (2008) identify this as a principal-agent problem. Gorton (2008) and Khandani et al. (2009) claim refinancing and the appreciation of home prices contributed immensely to the real estate crash; however, Goldstein (2017) argues that refinance did not play a critical role. Eventually, investors understood that the pools of mortgages being purchased may contain sub-prime mortgages and it was too late.

Researchers have also presented literature on how the international real estate markets operate and change over time by using agent-based simulations, such as the English housing market (Gilbert et al. 2009). I have included additional agents such as individual consumers and banks because their characteristics and behavior play critical roles in the market. In the U.S., ARMs typically rely on LIBOR, Treasury, and other financial indexes to represent an "interest rate." Although these rates do not drastically differ from the Fed funds rate, they are not identical values and do not represent the true components of adjustable-rate mortgages. I incorporate attributes belonging to individual people such as employment, income, etc. I also argue that changes in home prices, whether or not the property entered foreclosure, directly impact the property value of neighboring homes.

Foreclosure Discount and Contagion Literature

There is a variety of reasons as to why a borrower may involuntarily default on his/her mortgage such as unemployment, death, etc. Prior to a home legally entering foreclosure, it enters a stage called Real Estate Owned (REO), which allows the creditor (e.g., a bank) to retain full possession and then sell to another party. When a property enters REO and is no longer occupied, the property value may diminish due to neglecting maintenance, vandalism, squatting, and more (Harding, Rosenblatt, Yao, 2009; Rogers and Winter, 2009).Moreover, the property sells at an amount to cover the remaining balance of the mortgage.

Typically, it is in the interest of banks to work with borrowers on a plan for repayment because foreclosing a property leads to a bank not receiving the income it was anticipating over the life of the loan. Prior literature estimates the cost of foreclosure to range from $7,200 to $58,759 (Lin, Rosenblatt, and Yao, 2009; Rogers and Winter, 2009). As properties within a vicinity enter foreclosure, the neighboring property values diminish and lead to other properties foreclosing along with an increase in supply of homes available in the market.

This paper embeds the foundation of similar methodologies developed by Gangel et al. (2013a) to represent the contagion effect and contributes to real estate, foreclosure, and financial literature. Similarly, I incorporate a range of values determined by prior literature to measure the contagion effect. Researchers have claimed the contagion effect to range from 0.9% to a high of 8.7% (Immergluck and Smith, 2006; Lin, Rosenblatt, and Yao, 2009; Rogers and Winter, 2009). The literature has a consensus on the contagion effect being local among neighboring properties. I apply the range of 0.9% to 8.7% in the sensitivity analysis.

Prior to Gangel et al. (2013a), contagion effect models implemented a hedonic regression methodology to analyze the foreclosure contagion effect (Immergluck and Smith, 2006; Harding, Rosenblatt, and Yao, 2009; Lin, Rosenblatt, and Yao, 2009; and Rogers and Winter, 2009). As Gangel et al. (2013a) explains, "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." Gangel et al. (2013a) also build an agent-based model; however, agents only represent real estate properties and argue that disposition time and distance of properties are critical for understanding the contagion effect. I have included additional agents such as individuals/people and banks because their characteristics and behavior play critical roles in predicting the probability of a property entering foreclosure. I also argue that changes in home prices, whether or not the property has entered foreclosure, directly impact the property value of neighboring homes.

Interbank Contagion Literature

Upper (2011) summarizes literature focused on simulations estimating contagion and risk within the interbank loan market. As the author describes, there are various channels of contagion within the banking system. These channels may be related to the liability or asset side of the balance sheet. Upper provides a detailed summary of research affiliated with the different channels of contagion. For the purposes of this dissertation, I focus specifically on the direct effects from interbank lending; however, there is certainly opportunity to incorporate the multitude channels of contagion in future work. Given that one of the goals of this model is to contribute to methods for preventing contagion within the banking system, the decision to incorporate only one of the channels allows us to focus on the impact related to certain policy measures along with the opportunity to define precise implications.

I would like to address that I am not arguing that a single channel may lead to a bank failure or cause detrimental effects to the interbank market. Instead, I am claiming that the cumulative exposure to various channels may threaten the stability of these systems; therefore, it is important to incorporate modeling and monitoring techniques to mitigate risk. Upper and Worms (2004) claims that there is risk for domino effects within interbank lending if a safety net is not present; however, a safety net provided by institutions substantially reduces the risk of contagion. The authors state that the collapse of a bank may reduce up to 15% of total assets within a banking system. Contagious defaults have typically been prevented through government bailouts. Financial systems cannot solely rely on government bailouts as a prevention mechanism as it presents a serious moral-hazard concern and is not guaranteed to happen.

Direct default contagion is the theoretical concept that the occurrence of a default from one bank may spread a negative impact and risk to the balance sheet of another bank(s). Indirect contagion occurs due to channels aside from direct relations of the agents such as indirect effects related to changes in asset prices (Cifuentes et al., 2005; Fecht, 2004), or disinformation that may trigger a fear of losses among other agents. This may lead to a bank run thus potentially causing a negative impact to the asset side of a balance sheet (Dasgupta, 2004; Iyer and Peydró-Alcalde, 2005). Researchers have argued about whether the concept of default contagion truly presents danger and systemic risk to the interbank system. Elsinger et al. (2006) suggest that default-driven contagion within the interbank market does not necessarily play a major role, but the authors also emphasize that the robustness of their conclusion needs to be reviewed by using other datasets with additional observations and countries. Researchers have also discussed the different types of unexpected shocks that may negatively impact the banking system. These varying types include interest rate, exchange rate and stock movements, business cycles, credit, funding, and risk transfer shocks (Elsinger et al., 2006; Chan-Lau, 2010)

Allen and Gale (2000) demonstrate that the risk of contagion is dependent upon the completeness of the interbank system. According to the authors, structures react to the same type of shock(s) differently. A "complete" structure, one in which each agent is symmetrically connected to all relevant agents within the network, is significantly more stable than an "incomplete" structure where a node is only connected to a single node. "Disconnected" structures are also weaker than a "complete" structure when it comes to the spread of contagion; however, contagion does not impact every agent in the network. An additional structure is described by Freixas et al. (2000) where contagion may occur due to all additional agents that are linked to one centralized agent rather than each other. As Upper discusses, researchers have expanded on these theoretical frameworks by utilizing simulations to understand the risk of contagion in complex systems.

Chapter 3: Research Design and Methodology

There are various parameters that may be adjusted through the interface that impact the model's output, which are related to specific agents and the global environment. The initial density parameter determines the density of houses in the world. The rental-house density parameter determines how many properties are rental at tick 0, and the percent-occupied parameter generates the initial number of people. Furthermore, the elements within each agent rely on a random uniform distribution (i.e., income). People choose to live in affordable homes based on their available income to spend on a mortgage or rent. The tool outputs a variety of results, such as average house price, average mortgage cost, balance sheets of banks, real and natural unemployment rates, and more. Additionally, the "world" includes agents such as people, houses, banks and mortgages, and each tick represents a single month. Income and housing prices are in thousands of U.S. dollars. People can choose to rent or own one or more houses. Each house can either have a mortgage affiliated with a bank, or no mortgage at all. Figure 1 demonstrates the interdependent relationships among the agents and a high-level overview of their attributes.

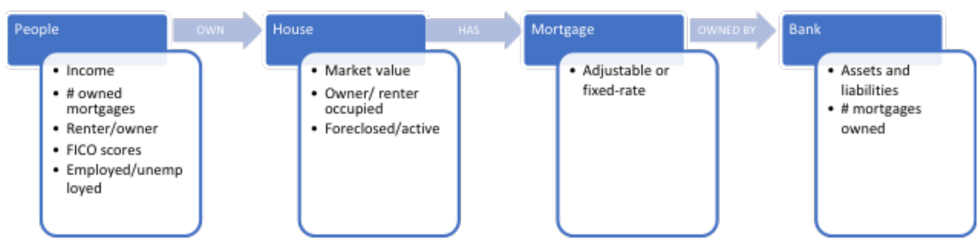

Fig. 1. Flowchart of the model, which lists entities, relationships and attributes at a high level.

I have chosen to import LIBOR 12-month forward curves to more accurately depict how these mortgages are modeled. LIBOR 12-month assumes that interest-rates will be adjusted every 12 months. For the sake of simplicity, I do not distinguish teaser and annual adjustable index rates pertaining to ARM loans for two reasons. First, there are several types of adjustable-rate mortgages (i.e., 5/1, 7/1, 10/1 etc.). The first number represents the number of years for the fixed teaser-rate; therefore, a 5/1 would represent a mortgage where the rate is fixed for five years, and then adjusts once every year for the life of the mortgage. The decision to not include these specific ARM products in the simulation allows for the observation of patterns between fixed and adjustable rate mortgages more clearly. Secondly, the model includes a mobility variable to account for the frequency and fraction of agents that move to different properties. This component allows the model to reflect the common behavior of homeowners selling their property just before the teaser-rate expires for ARMs. People choose to sell prior to the expiration of the rate, since ARMs tend to have lower initial rates than fixed-rate mortgages. Moreover, I have included both fixed and adjustable rate mortgages; however, the reader should note that majority of mortgages in the United States are fixed-rate products for 30 years. The next subsection will describe the various agents and variables within the model in-depth.

Agents and Variables

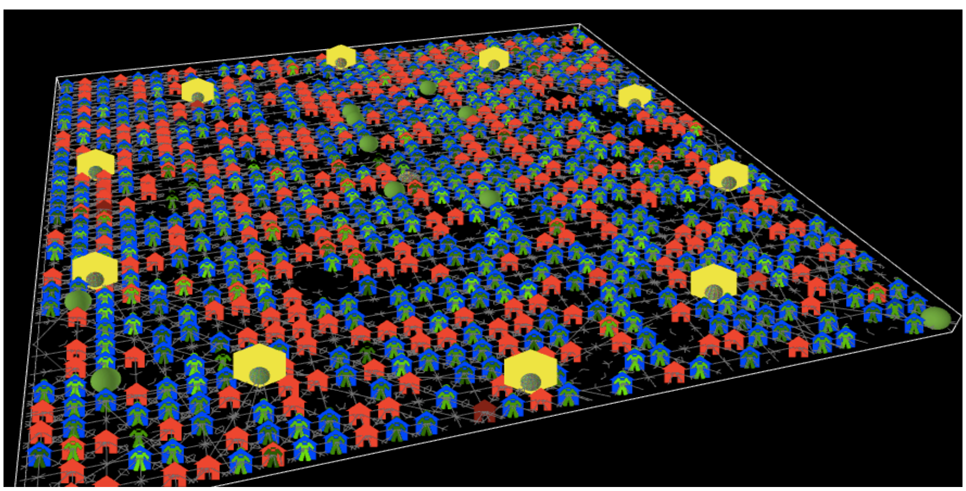

Fig. 2. Snapshot of ABM environment.

People. One category of agents in the model includes consumers (people), and every individual is randomly assigned an annual fixed income derived from a uniform distribution. These agents are also assigned credit (FICO) scores to determine the credibility of these borrowers. Additionally, people can be employed or unemployed throughout the simulation runs. If an agent is unemployed, its income is set to zero until it becomes employed again. The foundation for the unemployment portion of the model was adapted using components from Michal Kvasnička's NetLogo model, which is ultimately based on the traditional macroeconomic theory of unemployment. Every employed agent can lose their job with probability of the job-separation rate. In the same time, each unemployed agent searches for a job based on the probability of the job-finding rate. During recessions, the job-separation rate increases whereas thee job-finding rate decreases.

The wealth level of agents plays an important role throughout each simulation run. As displayed in Figure 2, shades of green depict a certain level of wealth where darker gradients represent high-income earners while lighter the opposite. Once the model initiates, agents assess their financial status to determine if they should relocate, own, or rent. People decide whether they can purchase a primary residence, and if not, they consider the option to rent. If an agent cannot afford any of the rental properties available at a specific time, it will leave the simulation. People can own more than one property if their capital investment permits, which provides opportunities to list the property as rental for others. Under the circumstance that an agent with more than one property cannot afford all of the mortgages, it will randomly sell one of the properties. The foundation of the consumer's decision to rent or purchase a property can be seen in Figure 3 below.

Houses. When the model is initiated, houses are randomly assigned a price, which follows a uniform distribution of $75,000-150,000. These agents use colors to depict whether a home is a rental (red), on the path to ownership (blue), foreclosed (pink), or vacant (black). A darker gradient of red or blue indicates a higher mortgage cost or rent. Links are used to create neighborhoods, which are constructed by establishing a maximum radial distance. I assume that properties undergo formal and informal appraisals of property value. Informal in the sense that an owner can determine an approximate appraisal value of the property by researching appraisal values of local and similar properties recently sold (Ling and Archer, 2009).

I also assume that neighboring properties have homogenous physical features, while individuals who occupy each property may differ based on a distribution. The change in appraisal values of neighboring properties may influence an agent's property value through links. Every month, a random percentage of agents will assess the appraisal value of their property by observing the change in property values of neighboring homes within a maximum distance assumption. The foreclosure discount is the negative percentage of price diminishment affiliated with foreclosed neighbors, and it is a function of the change in price and distance from an appraised property. It is notated by μ as displayed in formula below. The formulae below outline important variables within the ABM, which are important for quantifying the effect if a neighboring property has entered the foreclosure stage:

$$\Delta d_i = d_{max} - d_i, \qquad \Delta p_i = p_{\substack{i \\ t+1}} - p_{\substack{i \\ t}}$$

$$\text{Appraised Value}_j = p_j - \sum_{i=1}^{n} \mu \cdot \left(p_j + \frac{\Delta p_i}{\Delta d_i}\right)$$

where:

$\mathbf{\Delta d_i}$: difference between the i^{th} property and maximum distance constant (d_{max})

$\mathbf{d_i}$: distance from i^{th} property and appraisal property (j)

$\boldsymbol{\mu}$: contagion effect severity for a single home

$\mathbf{\Delta p_i}$: price change of i^{th} property from t to t+1

$\mathbf{p_j}$: price of appraisal property

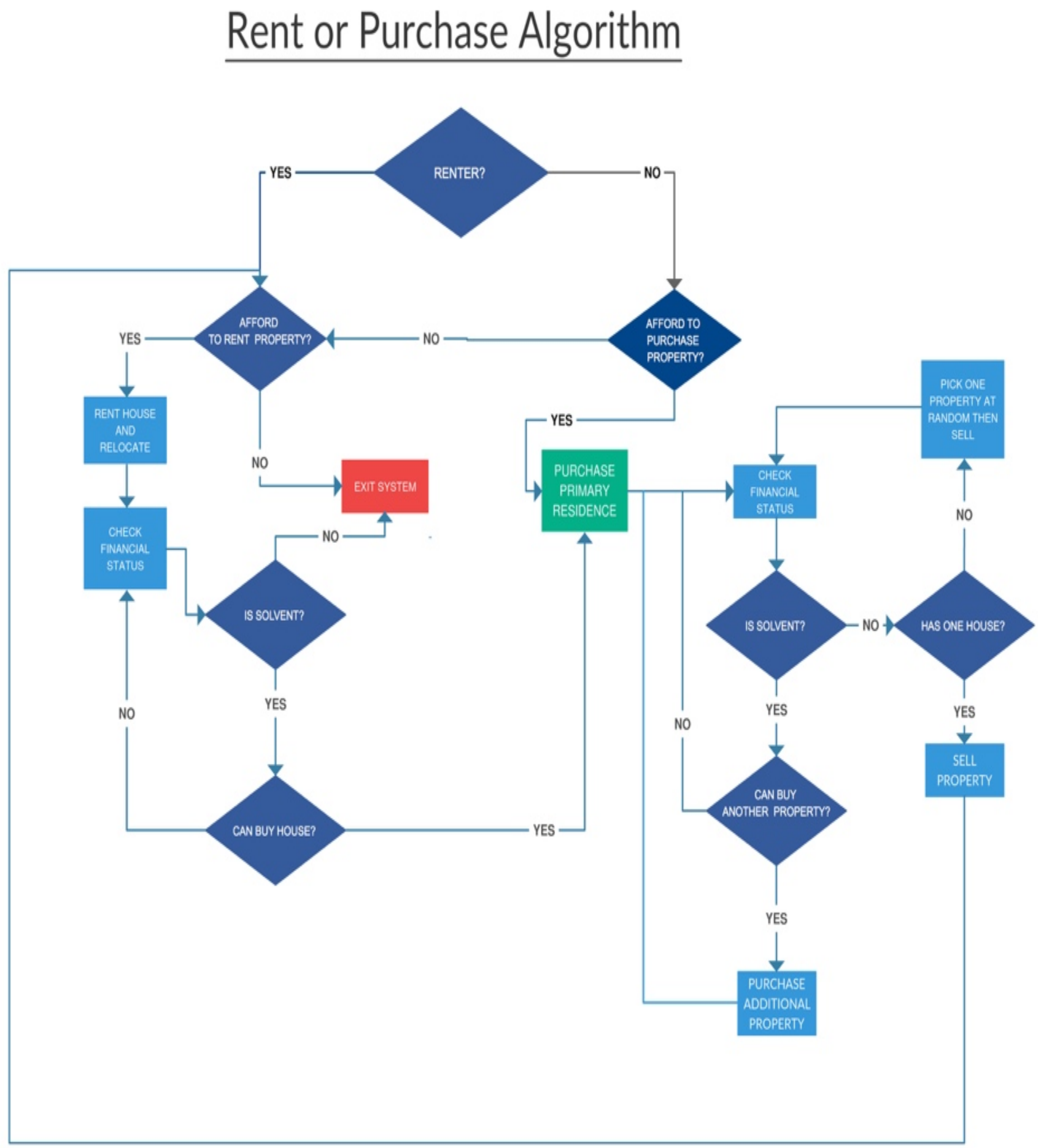

Fig. 3. Decision-making algorithm of agents for renting or purchasing properties. Visual adapted from McMahon, Berea, Osman (2009), which further demonstrates process of purchasing and selling multiple properties whereas pseudocode (Appendix) relates to renting or purchasing a primary residence.

Mortgages. Mortgages are another type of agent, which are owned and stored by banks; however, they are linked to a specific person and property. All loans include an interest rate, which is used to calculate individual amortization tables to determine monthly payments. A lag effect is introduced to account for people's reactions to changes in interest rates, which may lead to a re-finance opportunity. Moreover, only a random percentage of adjustable rate mortgages will respond to changes in interest rates. This will allow the simulation to properly model adjustable rate mortgages, where the interest rate is fixed for a specific amount of time and then adjusts to an indexed rate such as LIBOR. In a future version of the model, mortgages will be bundled together to create mortgage backed securities—a new product represented as an agent. People will also be able to prepay mortgages, which will rely heavily on probabilities from a predictive econometric model as the foundation.

Below is a table to demonstrate how ARMs, fixed-rate mortgages, and rent is calculated:

PRODUCT	EQUATION
ARM	$m = p\frac{r(1+(g+r))^n}{(1+(g+r))^n - 1}$
Fixed- Rate	$m = p\frac{f(1+f)^n}{(1+f)^n - 1}$
Rent	$t = p * c$

Table. 1. Summary of equations for calculating mortgage amortization tables and rent.

where:

m: monthly payment
p: principal amount (in this case, house price after down payment has been subtracted for mortgages)
r: index of choice (in this case, LIBOR 12-Month), which is also divided by 12 to represent your annual interest- rate
f: Fed-funds rate, which is also divided by 12 to represent your annual interest- rate
n: number of expected payments you will make for the life of the loan
g: For ARMs, this represents the additional spread or margin applied to the index rate
t: rent
c: fractional constant

This model also uses Cont's formula (2005) to represent the effect of aggregate demand on prices:

$$r_t = \ln \frac{S_t}{S_{t-1}} = g\left(\frac{Z_t}{N}\right)$$

where:

$\mathbf{r_t}$: return on house price at time t

$\mathbf{S_t}$: house price at time t

$\mathbf{Z_t}$: excess demand for houses at time t

N: number of agents

g(x) = x, which is the appreciation or depreciation of house price, can then be represented as excess demand by solving for S_t.

Banks. Each bank has a balance sheet to monitor its assets and liabilities, which is simultaneously initialized with the interbank network. These agents are connected with each other via links, which allows for the ability to incorporate risk exposures within the interbank market. Nonbank and interbank interactions contribute to the asset and liability side of each bank's balance sheet. External assets, which includes loans (i.e., mortgages) and securities to non-financial institutions and households, are captured within the assets side of the balance sheet. Each time an individual borrower reduces the principal balance of the loan by making a monthly payment, earning assets is reduced whereas cash is increased by this amount plus the interest payment. If a house undergoes foreclosure, this will negatively impact the assets portion of the balance sheet as the bank is not earning the interest dollars it expected over the life of the loan. Interbank assets include loans (earning assets) which are represented by edges that create the interbank network, and these assets are composed of cash as well. The liability side of the balance sheet is composed of deposits and interbank borrowing. Together, these factors contribute to the balance sheet of the bank agents.

The steps and equations below, which describe the initialization of balance sheets in the system, are heavily influenced by Nier et al. (2007) and Klinger and Teply (2014); however, I have revised the equations as the model presented in this dissertation contains several additional elements (e.g., mortgage-level products, non-financial agents, etc.). Table 2 below summarizes the parameters included within the balance sheet initialization and Table 3 summarizes the components that make up the balance sheet of an individual bank.

1) The model's total external assets (E) is calculated as: (1) the collective sum of unpaid principal mortgage balances and cash (M), which are initialized and calculated throughout the simulation as described in the previous sections and (2) securities plus additional external financial assets denoted as (Q). Securities and the other external assets are calculated by simply multiplying an input parameter percentage (p) by the aggregate value of each bank's mortgages and then summing the two components to ultimately derive the system's total external assets. The purpose of this is to account for the weighting and differentiation in size of each bank's balance sheet. The ratio of interbank assets to total assets θ is an input parameter, which allows total assets T to be calculated with respect to the initial aggregate value of external assets.

$$\mathrm{E} = \mathrm{M} + \mathrm{Q}$$

$$\mathrm{Q} = \mathrm{M} * \mathrm{p}$$

$$\mathrm{T} = \frac{(\mathrm{M} + \mathrm{Q})}{(1 - \theta)}$$

2) The aggregate value of interbank assets is therefore calculated using the equation below, which represents a percentage of the total assets in the system.

$$I = \theta T$$

3) The value of a single bank link s is calculated with respect to the total number of outgoing links U from all banks in the model.

$$s = \frac{1}{U}$$

4) Therefore, each bank's interbank assets i_i and liabilities v_i are determined based on their connections within the interbank network.

$$i_i = s * \text{total number of incoming links}$$

$$v_i = s * \text{total number of outgoing links}$$

5) Each bank's net worth n_i is ultimately defined as the delta between total assets and liabilities. Given that external liabilities have not been calculated at this stage, the model offers capital ratio γ as an input parameter which is then multiplied by the bank's total assets a_i to determine the agent's net worth.

$$n_i = \gamma * a_i$$

6) Finally, external liabilities (i.e., deposits) d_i are calculated to complete the balance sheet initialization.

$$d_i = a_i - n_i - v_i$$

Parameter	Interpretation
E = M + Q	Sum of external assets (mortgages and securities)
θ	Ratio of interbank assets to total assets
T	Total assets (external + interbank assets)
r	Erdös–Rényi probability
I	Sum of interbank assets
γ	Capital Ratio (Net Worth/Total Assets)
b	Number of banks

Table. 2. Dynamic parameters within agent-based model.

Assets	Liabilities
Interbank assets (i_i) External assets (e_i)	Interbank liabilities (v_i) External liabilities (d_i)
Total Assets a_i	**Total Liabilities** l_i
Net Worth n_i	

Table. 3. Components of an individual bank's balance sheet.

Incorporating Regulatory Requirements

Per federal regulation, banks are expected to meet liquidity requirements by retaining high quality liquid assets (HQLA), which can easily be liquidated in the market even during a time of stress. This requirement attempts to ensure that institutions possess enough regulatory capital to account for unanticipated events such as bank runs. The capital requirements for each bank are determined through multiple variables with a primary focus on the types of assets held by an institution and the associated risk. HQLA is typically composed of Level 1 and Level 2 assets where certain assets are subject to haircuts. Table 4 below distinguishes some examples of Level 1 and Level 2 assets.

Level 1 Assets	Level 2 Assets
Cash Marketable Securities	Certain securities and bonds Residential Mortgage Backed Securities (RMBS)

Table. 4. Components of Level 1 and Level 2 assets.

For simplistic and demonstrative purposes of this model, the tool assumes banks are holding Level 1 assets to avoid the application of haircuts. These assets are high quality and primarily liquid. The denominator, total net cash outflows, is defined as the delta between total expected cash outflows and inflows where outflows are represented as liabilities and inflows as contractual receivables.

Each tick, banks are constantly calculating their liquidity coverage ratios (LCR) to ensure they are obliging with the Basel Accords (i.e., Basel III). The LCR requirement was created in to make sure that banks are holding enough high-quality liquid assets to fund 100% of cashflows for 30 days, and it is broadly considered one type of stress test. For simplicity, The LCR can be summarized through the following formula where a value of 1 (100%) or greater demonstrates that the agent has met the liquidity requirement under Basel III:

$$LCR_i = \frac{High\ Quality\ Liquid\ Assets_i}{Total\ Net\ Cash\ Outflows_i}$$

Similar to Klinger and Teply (2014), the ABM is capable of testing for the effects of capital regulation within the model. In addition to the liquidity coverage ratio, banks are expected to meet a capital adequacy ratio (CAR), which is also formally known as the capital to risk weighted assets ratio (CRAR). Each tick, banks are monitoring their CAR to ensure they are compliant with regulation. If the ratio of a bank's net worth to its assets is less than the capital adequacy ($\frac{n_i}{a_i} <$ CAR), the bank exits the system (similar steps as if it defaulted), which translates to the removal of the agent by regulators as it is non-compliant. First, the bank sells its assets to repay external liabilities, and then its interbank liabilities. Under the condition that a bank cannot repay its inter-bank liabilities, it transfers the loss to the creditor banks. Secondly, the system must account for claims of debt owed by other banks. The model assumes that these claims are sold to an agent that is exogenous to the model; therefore, the amount of interbank liabilities owed to the non-compliant bank is transferred to the external liabilities portion of the balance sheet. The following pseudocode in Figure 4 summarizes these steps:

```
Capital Regulation – Non-Compliance

  For each bank
    If the ratio of net worth to total assets < capital adequacy ratio requirement
      Implement non-compliant rules below, and then exit system:

Transfer of Claims from Non-Compliant Bank to Creditors

    Sell assets and first repay external liabilities
    Then repay interbank liabilities
    If bank cannot repay interbank liabilities
      Uniformly transfer loss to creditor banks

Transfer of Claims from Debtors

    If bank is linked to non-compliant bank as debtor
      Convert interbank liability amount to external liability
```

Fig. 4. Pseudocode describing steps for incorporating regulatory requirements (i.e., capital regulation).

Additionally, as Klinger and Teply (2014) describe, the capital adequacy ratio (CAR) cannot be set as an input parameter given that the initial capital ratio γ is already an input parameter and varies during the parameter sweeps and sensitivity analyses. Thus, CAR can be determined by the following formula where r_i represents the removal ratio and it is a binary variable:

$$r_i = \frac{CAR_i}{\gamma_i}$$

The CAR requirement is expressed as a percentage of the initial capital ratio. A value of 0 means that no banks cannot be removed as regulatory enforcement is not present. A value of 1 corresponds to the initialized capital being equivalent to the CAR requirement, and the ability for regulators to remove banks exists. Therefore, a bank will exit the system if its capital ratio is below the initialized level.

Types of Shocks

Within the ABM, there are different types of shocks that may occur within the system. At the people level, shocks may be introduced which impact levels of unemployment. Each time a shock scenario is applied, the "job finding" and "job separation" rates are impacted. The job separation rate is the probability of an individual person becoming unemployed, and the job finding rate is the probability of an unemployed person becoming employed. Under the recession scenario, the job finding rate is decreased which translates to a lengthier job search related to the difficulties of seeking employment during recessions, and the job separation rate is increased to represent a high probability of layoffs. Under the high welfare scenario, unemployment benefits are increased; therefore, people may be more inclined to reject job offers or take more time to find a job, and the job finding rate is decreased. Under the low welfare scenario, unemployment benefits are decreased; therefore, people are actively searching for immediate employment and the job finding rate is increased. Finally, the good times scenario implies that unemployment benefits and job finding and separation rates are at a regular level (i.e., the average between the high and low welfare scenarios). Under the economic boom scenario, a percentage of people experience an increase in their income. This percentage is dynamic and can be adjusted while using the tool or during sensitivity analyses.

According to Bookstaber (2012), an agent-based model focused in this area "…should allow for the range of shocks that are typical in causing and propagating a crisis. These include a seizing up of liquidity; a fire sale in the face of forced deleveraging with the subsequent funding and liquidity effects; a sudden funding impairment, which is often brought on by a shock to real or perceived credit worthiness or liquidity; or in the extreme case, the failure of a firm posed as an exogenous event." Moreover, similar to Klinger and Teply (2014) and Nier et al. (2007), I incorporate the concept of shocks within the interbank system with a few caveats to represent the range of shocks. There are two types of shocks within the system: (1) local and (2) global. Local shocks translate to a dynamic portion of a single random bank's external assets (non-mortgage portion) being removed from the balance sheet. These can be thought of as shocks related to operational risk such as fraud and credit risk. They are classified as idiosyncratic shocks given that one bank is shocked at a time, which potentially leads to knock-on defaults for the other banks. First, the initial shock is applied during the simulation to a random bank i which is then identified as the source. The size of the shock is reflected as a percentage of the bank's external assets, and this percentage is an adjustable parameter. When the source has recognized that a shock has been applied, the bank absorbs the shock in the following order: (1) net worth (2) interbank liabilities and (3) its deposits. As Nier et al. (2007) describe, this logic implies that consumer deposits are senior to interbank deposits, which are senior to equity (i.e., net worth). If the size of the initial shock t_i is greater than bank i's net worth n_i, then the source bank will ultimately default. Proceeding the absorption of the initial shock through the source bank's net worth, if the residual loss is less than the interbank liabilities v_i owed by the source bank (t_i - n_i < v_i), then this residual loss is transferred to the total number of creditor banks c linked to the source banks. If bank j is a creditor bank receiving such loss t_j, then the value of this loss is calculated as:

$$t_j = \frac{t_i - n_i}{c}$$

Furthermore, if the residual loss is greater than the interbank liabilities owed by the source bank (t_i - n_i > v_i), then the remainder of the loss is transmitted to the depositors (t_i - n_i - v_i). If the creditor bank does not withstand the shock through its net worth ($t_j \leq n_j$), then the creditor will default due to the contagious effects and will enter the same process previously described until the shock is completely absorbed. Figure 5 presents pseudocode, which elaborates on the step-by-step process related to the source bank formally. Global shocks translate to a decrease in external assets of all banks; therefore, all banks experience a percentage loss to their balance sheets.

Shock Transmission from Source Bank – Interbank Network

Ask $bank_i$ (source bank of initial shock)
If size of $shock_i$ > net $worth_i$
Then ask $bank_i$ to default
If the residual loss from the shock (size of $shock_i$ - net $worth_i$) < $bank_i$ interbank liabilities
Then transfer the value of the residual loss to the creditor banks
If the residual loss > $bank_i$ interbank liabilities
Then transfer remainder of loss to depositors (size of $shock_i$ - net $worth_i$ - $bank_i$ interbank liabilities)
Else reduce net $worth_i$ by size of $shock_i$

Fig. 5. Pseudocode describing steps for incorporating initial shock and its impact.

Types of Foreclosures

I embed the different foreclosure effects influenced by Gangel et al. (2013a) within the model. Below is a summary description of each type of foreclosure along with the pseudocode (Figure 4).

Equity Foreclosure. I calculate an equity ratio using the current appraisal value and outstanding principal balance. If the equity ratio is below one, then the borrower acknowledges the presence of an underwater mortgage, which leads to an increased probability of the owner defaulting.

Let C_{equity} be equal to a constant that reflects the effect of the equity ratio:

$$Equity\ Ratio = \frac{Appraised\ Value}{Unpaid\ Principal\ Balance}$$

If Equity < 1,

$$Equity\ Foreclosure\ Effect = \frac{(1 - Equity\ Ratio) * C_{equity}}{Unpaid\ Principal\ Balance}$$

If Equity ≥ 1,

$$Equity\ Foreclosure\ Effect = 0$$

Interest Rate Foreclosure. As previously mentioned, the ABM includes both fixed and adjustable rate mortgages. Fixed rate mortgages are not prone to interest rate foreclosures because the borrower has agreed to an affordable mortgage; however, ARMs are the opposite. After the fixed-rate period expires, the interest rate resets annually following LIBOR 12-month rates in this environment. An increase in interest rates leads to higher payments, which increases the probability of default whereas a decrease in rates reduces the probability of default. Let C equal a constant that reflects the effect of the probability of interest rate foreclosure, and let IC equal the percentage change between the prior and current monthly payments:

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

$$Interest\ Rate\ Foreclosure\ Effect = \frac{(IC - 1) * C}{12}$$

Investor Foreclosure. An investor is likely to voluntarily ignore their mortgage obligation even when the investor can afford to make payments (i.e., exercise one's put option) if the renter's payment is below the monthly mortgage payment. While Gangel et al. (2013a) do not focus on the renter market, I chose to include these agents in the simulation; therefore, I can more accurately represent the investor foreclosure effect. Let $C_{investor}$ equal a constant that reflect the effect of the probability of an investor foreclosure:

Rent < Mortgage,

$$Investor\ Foreclosure\ Effect = \frac{C_{investor}}{12}$$

Rent > Mortgage,

$$Investor\ \text{Foreclosure Effect} = -\frac{\mathrm{C_{investor}}}{12}$$

Catastrophic Foreclosure. A catastrophic event such as job loss may lead to an increase in the probability of foreclosure. Gangel et al. (2013a) simply include a constant to represent the probability of a foreclosure due to a catastrophic event; however, I only include this constant if the individual person is actually unemployed in the simulation. Let $C_{catastrophic}$ equal a constant that reflects the probability of foreclosure from becoming unemployed.

Total Probability of Foreclosure. I have described the different types of foreclosure effects, which ultimately calculate a final probability of a property entering foreclosure based on characteristics pertaining to individual mortgages, homes, and people. The table below summarizes how each type of foreclosure effect is calculated depending on whether the property is owner/renter occupied and whether the mortgage has a fixed or adjustable rate.

Type	FRM	ARM
Owner-Occupied	Equity, Catastrophic	Equity, Interest Rate, Catastrophic
Rental/Investment	Equity, Investor, Catastrophic	Equity, Interest Rate, Investor, Catastrophic

Table. 5. Summary of foreclosure effects.

As an illustrative example, below is the foreclosure probability for an owner-occupied property with an affiliated ARM loan and unemployed owner:

$$\begin{aligned}&P(\text{Foreclosure} \mid \text{ARM, Owner-Occupied})\\&\qquad = \text{Equity Foreclosure Effect} + \text{Interest Rate Foreclosure Effect} + C_{\text{investor}}\end{aligned}$$

```
Calculating Probability of Foreclosure

  Catastrophic Foreclosure
  If home-owner is unemployed
   Apply catastrophic-effect foreclosure constant

  Equity Foreclosure
   For each property
      If Unpaid Principal Balance  > 0
        Set Equity-Ratio as (Property Value / Unpaid Principal Balance)
      If Equity-Ratio < 1
        Set Equity-Effect as (1 - Equity-Ratio) * Foreclosure-Constant / 12
      Else
        Set Equity-Effect as 0

  Interest Rate Foreclosure
    If Type-of-Mortgage is "ARM" and delta to next tick mortgage cost is > 0
      Set Interest Rate ChangeEffect as Interest Rate Change * foreclosure-constant / 12

  Investor Effect Foreclosure
   If property is a rental  and rental income < Mortgage Cost
      Set Investor-Effect as Foreclosure-Constant / 12
   Else
      Set Investor-Effect as (-1 * (foreclosure-constant / 12))

   ; Calculate Total Probability of Foreclosure
```

Fig. 6. Pseudocode describing how the model determines the different types of foreclosure effects.

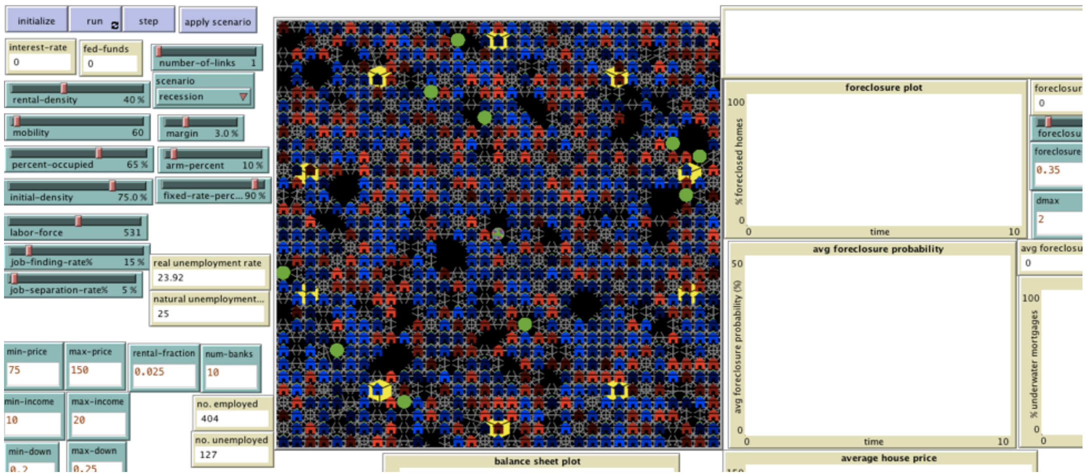

Fig. 7. Screenshot of interface

Chapter 4: Results

Baseline Run: Focus on People and Houses

This section of the dissertation will discuss baseline runs of the model with applied "shocks" to generally demonstrate how it performs over time. Given that the tool offers several dynamic parameters and focuses related to the different agents, I have split the portion of the model related to banks into a separate section to elaborate on the model's aspects and capabilities more in-depth. The baseline scenario is initialized using the default parameter settings, and the goal is to replicate similar trends pertaining to the housing prices and foreclosure effects during the Financial Crisis. Figure 7 is a screenshot of the interface after it has been initiated in NetLogo.

In this scenario, I have set the fixed-rate mortgage population to 90% of the pool because most mortgages in the United States are in fact fixed-rate as opposed to adjustable-rate. I have also set mobility to 60 ticks (i.e., 5 years) and agents may move at any random tick below that threshold. Moreover, this will allow us to calibrate towards the behavior of 5/1 ARM homeowners, since individuals tend to move after the teaser rate has expired. People can place anywhere from a 10-25% down payment on their mortgage(s) representing the average range in the United States. I have set the foreclosure effect constant to be 35% for all of the types of foreclosures that can occur, which suggests that any of these effects have the same impact on the probability of foreclosure. The complete probability of a foreclosure must be equal to or greater than the threshold of 40% for this iteration, and/or 3 months delinquent on payments. Americans are typically 90 days delinquent on payments before a home enters into the real estate owned (REO) stage. Additionally, the contagion effect for a neighboring home that enters a foreclosure is 8.7%, which is the upper estimation from prior literature. The neighborhoods are in a maximum radial distance of 2 patches to represent local communities with similar demographics. As the simulation begins from January 1986 (time 0) and runs until January 2000 (169 ticks), the average foreclosure property has remained quite flat compared to the initiation of the model, but the percentage of foreclosed homes has certainly fluctuated. Figure 8 displays three graphs, which include: average foreclosure probability, Federal Reserve rates, LIBOR, and the average house price. House prices drastically rose from 1986-2000. Just before the year 2000, there is a dip in the average house price with a slight recovery. Fed funds rate and LIBOR have diminished significantly since the initialization of the model, and these rates are leveraged and assigned to mortgages over time.

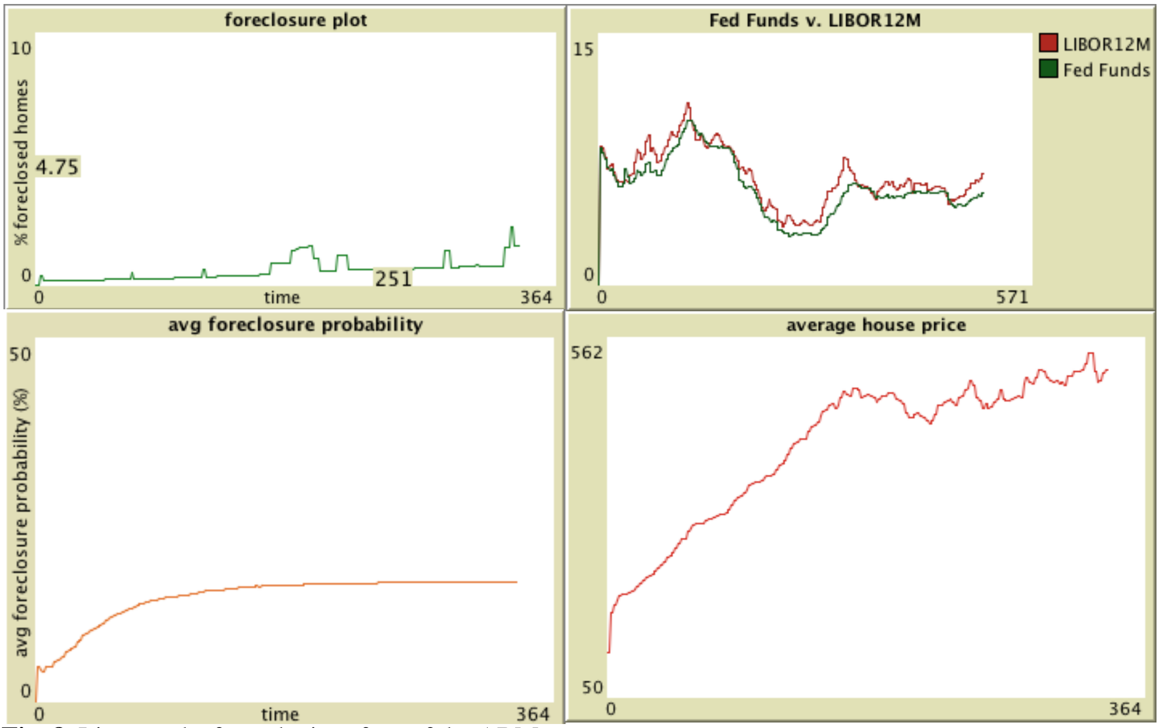

Fig. 8. Line graphs from the interface of the ABM.

By the time the model reaches September 2001, I introduce two "shocks" to the baseline run: (1) a recession shock and (2) low welfare benefits. This is to account for a 9/11 political shock, which severely impacted the economy. Although arbitrary, the effects from the shock last until January 2004, which is after George W. Bush was elected as President of the United States for his second term. Figure 9 displays that interest-rates continue to remain at an all-time low, and average price of homes are at an all-time high.

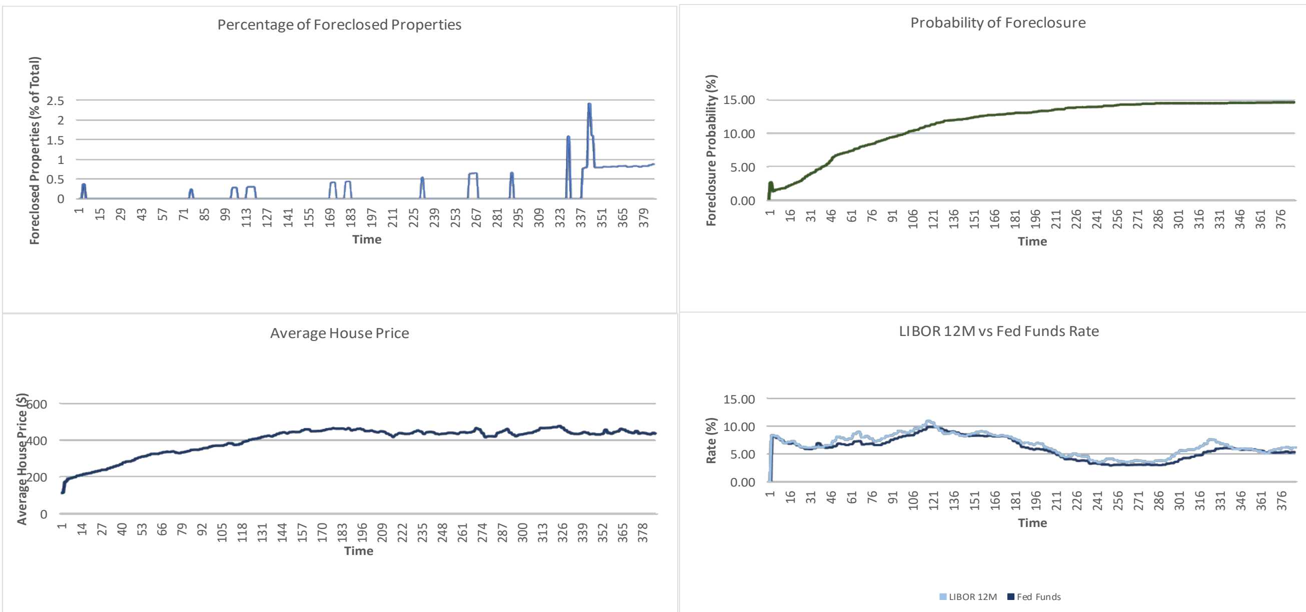

Fig. 9. Update of graphs by January 2004.

I continue to run the model until approximately Fall 2007 and characteristics of the upcoming financial crisis become apparent. At this period, the average house price peaked and entered a severe dip representing the burst of the housing bubble. Figure 10 displays the average house price until April 2017. In this run of the model, the average house price remains extremely high compared to historical prices. There is also a spike in the percentage of foreclosed properties further demonstrating the foreclosure contagion effect and delinquent payments. Below is an additional screenshot to see projections of foreclosed homes in 2023 (Figure 11).

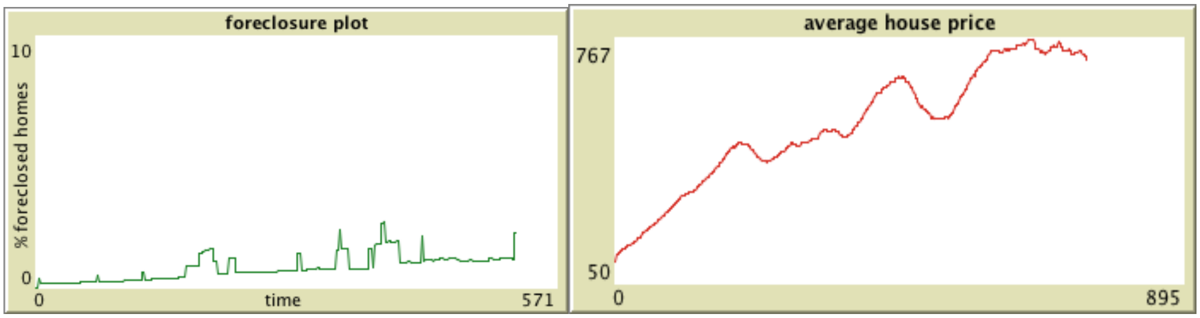

Fig. 10. Average house price by April 2017 and percentage of foreclosed properties.

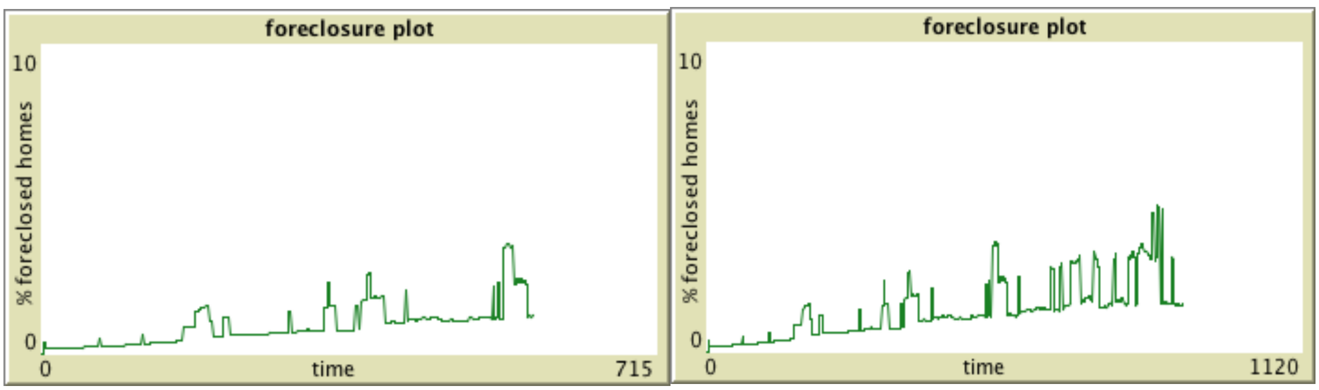

Fig. 11. Percentage of foreclosed properties in 2009 (left) and 2023 (right).

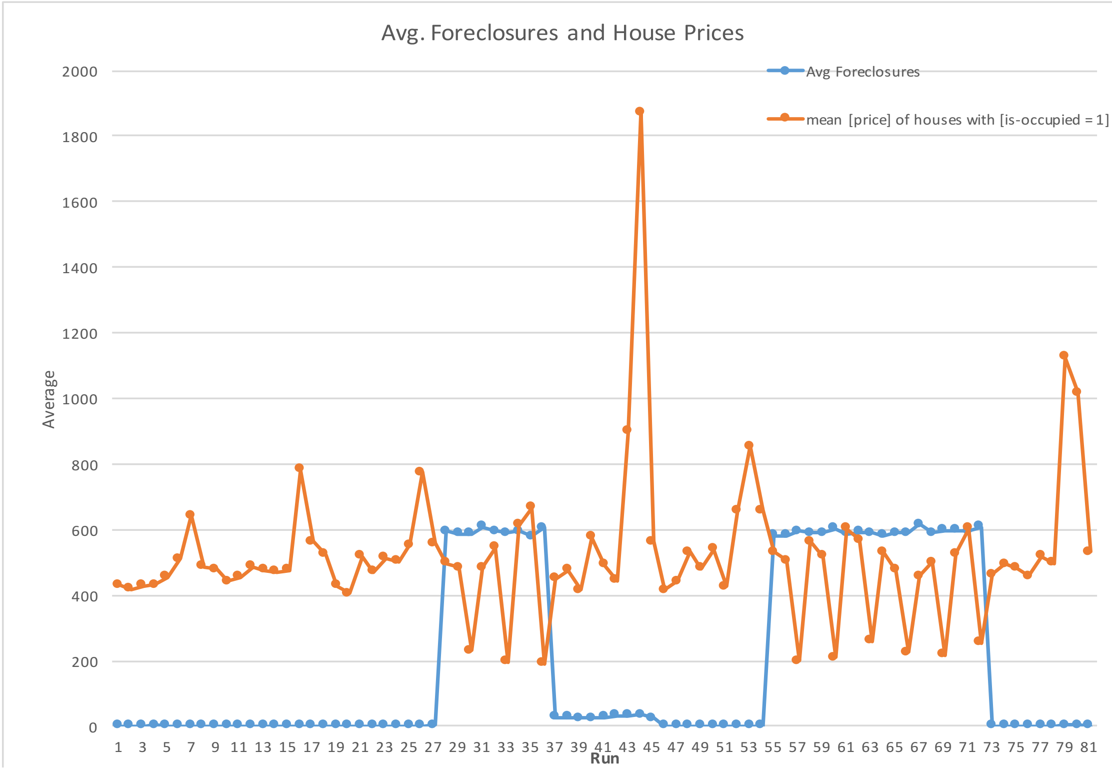

Fig. 12. Average foreclosures and house prices during sensitivity analysis.

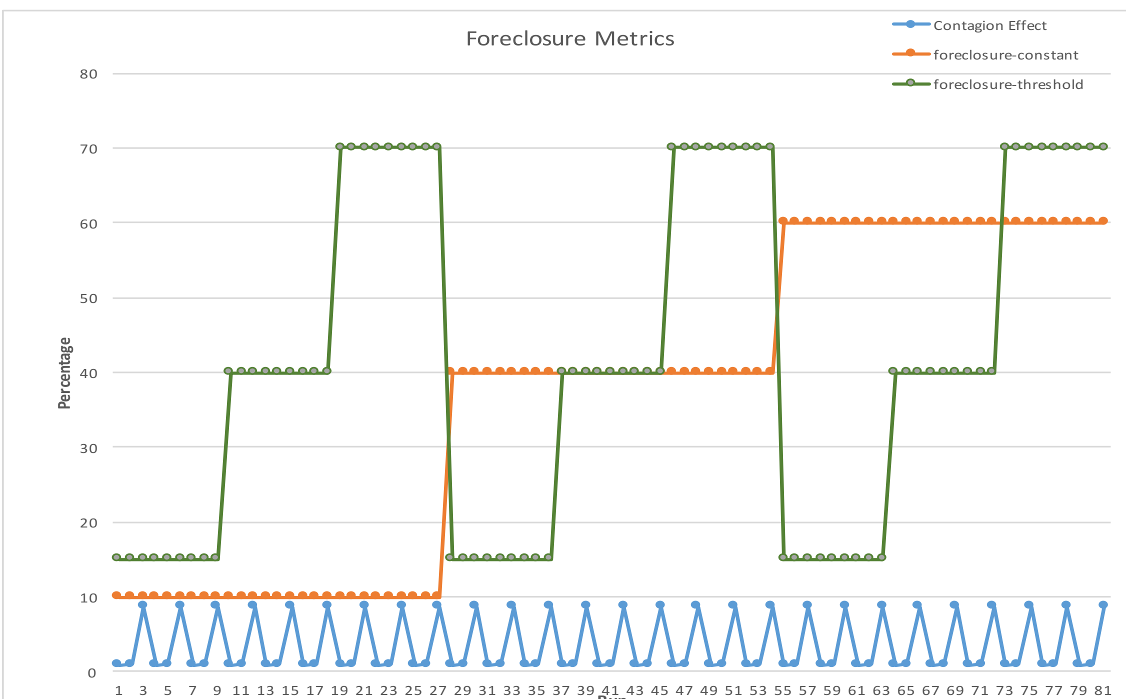

Fig. 13. Variation of foreclosure parameters for sensitivity analysis.

Sensitivity Analyses: Focus on People and Houses

I ran 81 different scenarios by using the BehaviorSpace (i.e., parameter sweeping) feature in NetLogo to perform behavioral experiments and run sensitivity analyses on housing prices and the foreclosure contagion effect using approximately 31,000 generated observations. Three output variables are measured which may operate as dependent variables to measure the effects from the foreclosure contagion effect along with additional consumer-level attributes and emergent behavior. The variables include average mortgage, average house price, and total foreclosed properties. This feature allows the user to list varying values for each parameter to gain a more concrete understanding. Above, Figure 12 plots the average house prices of each property and the average number of foreclosed homes during each simulation run. Figure 13 displays the inputs for the different foreclosure parameters per simulation run. Table 6 provides descriptive statistics and correlation of the dependent variables.

Dependent Var.	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Average Mortgage	31,023	1.277251	0.5862547	-6.060171	3.743937
Average House Price	31,023	519.8349	392.6365	-941.5159	9107.49
Total Foreclosed Properties	31,023	75.5025	113.6511	0	529

Dependent Var.	**Average Mortgage**	**Average House Price**	**Total Foreclosed Properties**
Average Mortgage	1.000		
Average House Price	-0.304	1.000	
Total Foreclosed Properties	0.187	-0.304	1.000

Table. 6. Descriptive statistics and correlation of dependent variables.

VARIABLES	(1) Total Foreclosed Properties	(2) Average Mortgage	(3) Average House Price
Foreclosure constant	782.6***	-0.167***	-9.618
	(4.551)	(0.0151)	(7.319)
Foreclosure thresh.	-715.5***	0.131***	208.9***
	(4.061)	(0.0137)	(7.458)
Max Radial Distance	1.610	-0.0395***	110.3***
	(1.145)	(0.00436)	(3.072)
Contagion effect	14.21	-2.920***	-2,165***
	(25.82)	(0.0857)	(44.61)
Constant	209.0***	1.466***	292.2***
	(3.556)	(0.0118)	(6.594)
Observations	31,023	31,023	31,023
R-squared	0.654	0.042	0.108

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Fig. 14. Pooled regression results.

Figure 14 shows regression results for the pooled regression. Each dependent variable is regressed on the same independent variables. The first column indicates that the foreclosure constant has a positive effect on the total number of foreclosed properties while an increase in the foreclosure threshold has a negative effect as expected. Distance between houses does not play a critical role here. The second column regresses average mortgage in the world on the key independent variables. When the data is pooled together, an increase in the foreclosure constant, maximum distance radius and contagion effect each independently have a negative impact on the average mortgage cost. As expected, this indicates that there is more supply in the market along with lower house prices thus reducing the mortgage cost because the probability of foreclosure among neighboring homes increases; however, an increase in the foreclosure threshold has a positive impact on average mortgage cost because homes are less likely to enter foreclosure.

Similarly, the third column regresses average house price on the independent variables of interest. An increase in the contagion effect has a negative impact on average house prices, which truly demonstrates the foreclosure contagion effect. Property values tend to stay high with increases in the foreclosure threshold and the maximum radial distance. The maximum radial distance has a positive impact on average house prices because neighboring homes that have not entered foreclosure influence a given property.

Furthermore, I ran another 288 different scenarios by using the BehaviorSpace (i.e., parameter sweeping) feature in NetLogo to perform behavioral experiments and run sensitivity analyses on housing prices using over 110,000 generated observations. Table 7 below summarizes the setup and randomization of parameters for the iteration to compile a total of 288 runs.

percent-occupied 65	arm-percent 10 30	min-down 0.2	min-income 10
rental-density 40	mobility 60	rental-fraction 0.025	job-finding-rate% 10
max-down 0.25	max-income" 0.20	margin 3 10	initial-density 75
min-price 75 100 125	job-separation-rate% 5	num-banks 5 15	fixed-rate-percent" 90 70
max-price 150 175 200	foreclosure-constant 0.35	foreclosure-threshold" 0.4	contagion-effect 0.009 0.087

Table 7. Setup for the 288 simulation runs

Three output variables are measured which may operate as dependent variables to measure the macro-political economy of the housing market. The variables include average mortgage and average house price. Below, Figure 15 plots the ending average house price of the population against the initial minimum and maximum house prices and average mortgages. The scatter plot in the bottom-left quadrant represents the phenomenon of underwater mortgages. Typically, one would expect a positive relationship between higher property values and mortgage costs; however, our sensitivity analysis demonstrates that many individuals at the end of each simulation run had very high mortgage costs for houses with low property values on average.

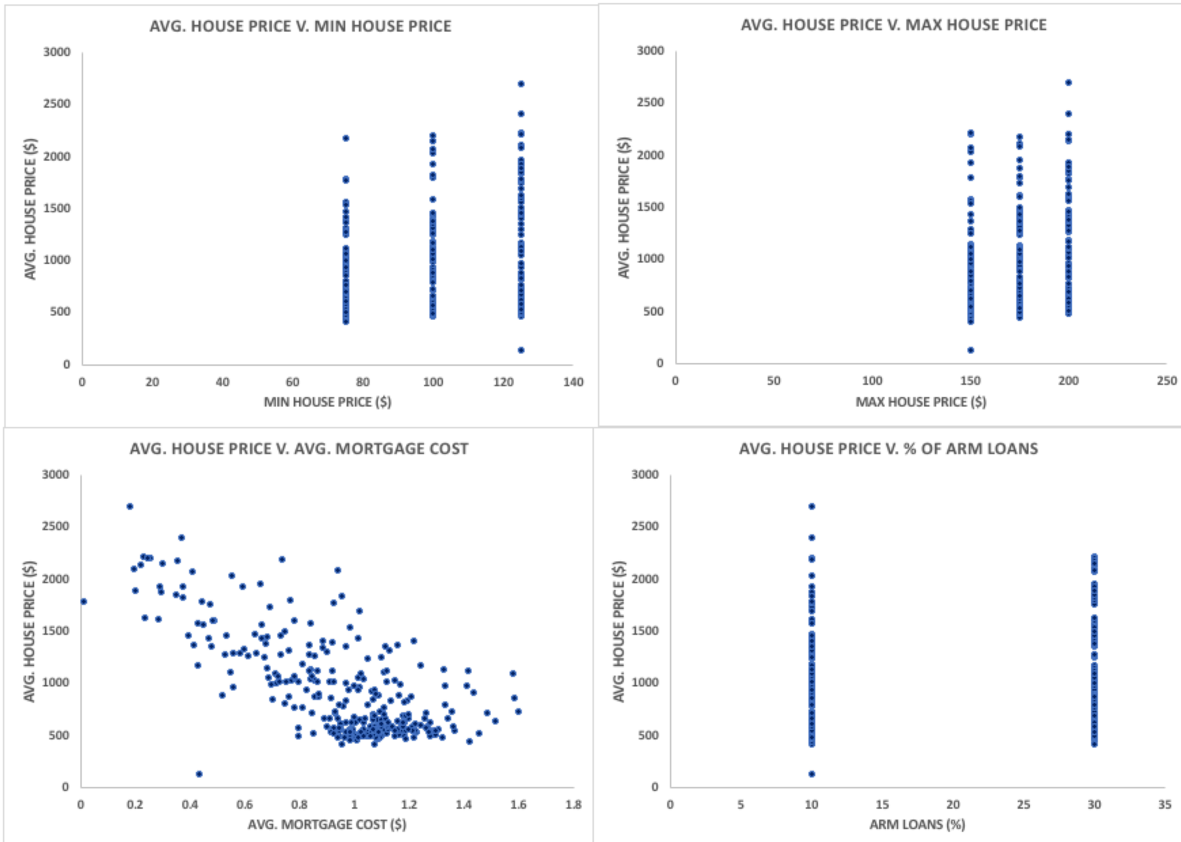

Fig. 15. Average foreclosures and house prices during sensitivity analysis.

Figure 16 shows a panel of time series plot of core outcome variables from the sensitivity tests. The price of occupied houses keeps increasing over time, though at different pace: fast at the beginning period and ending period of the simulation, but slower in the middle. Average mortgage cost shows a completely different pattern. It climbs at the beginning and reaches the peak very fast, fluctuates at the high level until the time period when house price starts to rapidly increase, then decreases with some fluctuation. The number of banks with income from houses stays at the same level across the entire simulation period after the very first few iterations when actions are taken place. The number of people with no investment capital has the largest fluctuation. However, as expected, this fluctuation follows the trend in average mortgage cost. After the mortgage cost peaks, when it goes high, the number of people with no investment capital also peaks.

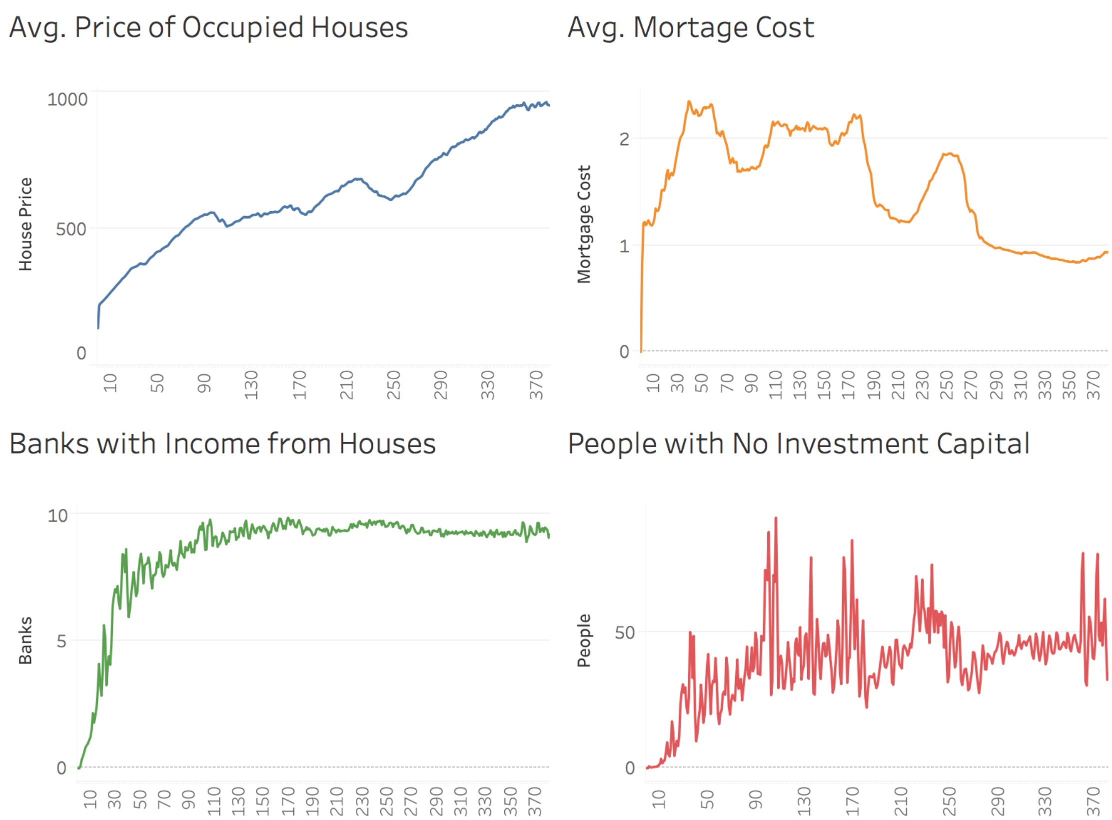

Fig. 16. Time series plot for core variables from sensitivity analysis.

Below, Table 8 quantifies the correlation between some of the important variables included in our agent-based model. The average house price and mortgage cost have a strong negative relationship, which further illustrates that higher property values do not necessarily imply a higher mortgage cost. The population of ARMs versus fixed rate mortgages was adjusted throughout the sensitivity analysis; therefore, exceedingly high mortgage costs may be attributed to an increase of the ARM population along with the spike in interest rates this product exhibits once the teaser rate expires. Additionally, this sensitivity run highlights the dilemma of underwater mortgages, which may lead to an increased probability of delinquent payments and eventually foreclosure.

Dependent Var.	Average Mortgage	Avg House Price
Average Mortgage Cost	1.000	
Average House Price	-0.4769	1.000
Minimum House Price	0.0520	0.1554
Maximum House Price	0.0657	0.1318

Table 8. Correlation of variables.

Figure 17 shows the pooled regression results from our generated data. The results indicate that increases in initial minimum and maximum house prices lead to higher house prices on average regardless of how the agents behave and adjust their goal-oriented decisions. To reiterate, houses tend to be an asset that appreciates over time; therefore, an increase in the initial minimum and maximum house price will lead to a higher peak when assessing the property values in the world. This demonstrates the sensitivity of the initial input values for these variables, and the significance of understanding the property value distribution in a specific geography when we analyze the real world. Moreover, an increase in the percentage of adjustable rate mortgages tends to influence higher house prices on average, whereas an increase in fixed rate mortgages presents the converse. ARM products tend to be more affordable than fixed rate mortgages in the short run; therefore, an increase in the availability of these products to consumers will increase the ability and demand to purchase a home, which will increase the overall property values in the specific "neighborhoods" of the world. As displayed in the results, an increase in the population of fixed-rate mortgages tends to have a negative impact on house prices given that these products are more expensive; therefore, reducing demand.

VARIABLES	Average House Price
Min. House Price	2.188***
	(0.0386)
Max. House Price	1.856***
	(0.0379)
ARM (%)	0.388***
	(0.0770)
Fixed Rate (%)	-11.74***
	(0.0770)
Constant	1,013***
	(8.775)
Observations	110,299
R-squared	0.209

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Fig. 17. Pooled regression results.

Comparative Static Simulation Runs: Focus on Banks and Interbank Network

The primary parameters within the model for constructing the banking system each simulation include: net worth as a percentage of total assets (i.e., capital ratio) (γ), the percentage of total assets related to interbank assets (θ), the Erdös–Rényi probability of 2 nodes being connected if this feature is used (r), and the number of banks (b). Given the granularity of the model by incorporating mortgage products, I do not keep external assets fixed as Nier et al. (2007) does. The agent-based model presented in this dissertation includes several more agent types (i.e., houses, people, and mortgages, along with their respective attributes) and sensitivity analysis parameter combinations than prior agent-based models related to this topic. For example, this agent-based model is capable of combining the phenomena of both foreclosure and interbank contagion. Moreover, the parameters related to houses and people follow the baseline parameter settings described in the previous relevant section. This allows for mortgages to be modeled similarly to how financial institutions model these products, which allows you to assess risk for each individual mortgage throughout the life of the product. In other words, the loan supply in the market is not fixed.

Financial institutions are absolutely capable of creating a wide variety of financial products; therefore, it is important for such simulation models to be capable of including such products as they are created for different reasons (e.g., ARM products intended for individuals in a house for a specific period). Given that this section is the baseline or benchmark run with varying parameters, I will follow Nier et al.'s experimental methodology on focusing on comparative static; therefore, these will be experiments where a single parameter is varied at a time but I will also report on situations where two parameters are simultaneously varied. Note that this section will not focus on the regulatory aspects of the model and will be demonstrated in the following section. Additionally, interest rates will not be flowing from the Federal Reserve's federal fund rates nor the LIBOR curves. Instead, the model will randomly assign interest rates within a range (3%-7% for the benchmark experiment to include mortgages that may have been assigned high rates during a specific time period). Adjustable rate mortgages will have their rates reassigned within the same range as well.

As benchmark criteria, the parameters will contain the following values unless the parameter is of focus to be varied: net worth as a percentage of total assets ($\gamma = 5\%$), percentage of interbank assets related within total assets ($\theta = 20\%$), Erdös–Rényi probability ($r = 20\%$), number of banks (i.e., nodes) ($b = 25$). As mentioned above, I will vary one of these parameters per experiment while keeping the other parameters fixed. Table 9 provides a list of parameters and their corresponding value(s) under the benchmark criteria and variation range.

Parameter	Benchmark	Sensitivity Range
Net worth	5%	1-10%
Erdös–Rényi probability	20%	10-100%
Percentage of interbank assets	20%	0-50%
Number of banks	25	10-25

Table 9. Parameter benchmark values and variation ranges.

The model runs for 50 ticks per simulation with a given combination of parameters to allow for the balance sheets to be calculated, and then the local shock is applied before the final tick. The initial shock is calibrated to clear out 100% of external assets for the chosen bank to align with Nier et al.'s calibration. Additionally, this will also allow us to see how the likelihood of contagious defaults may differentiate when external assets are not a fixed parameter and instead calculated using differentiating behavior at the agent-level (e.g., people, mortgages, houses). For each combination of parameters, I repeat this exercise 10 times and then report based on averages. This will allow us to analyze how many of the banks defaulted while varying the specific parameter of focus.

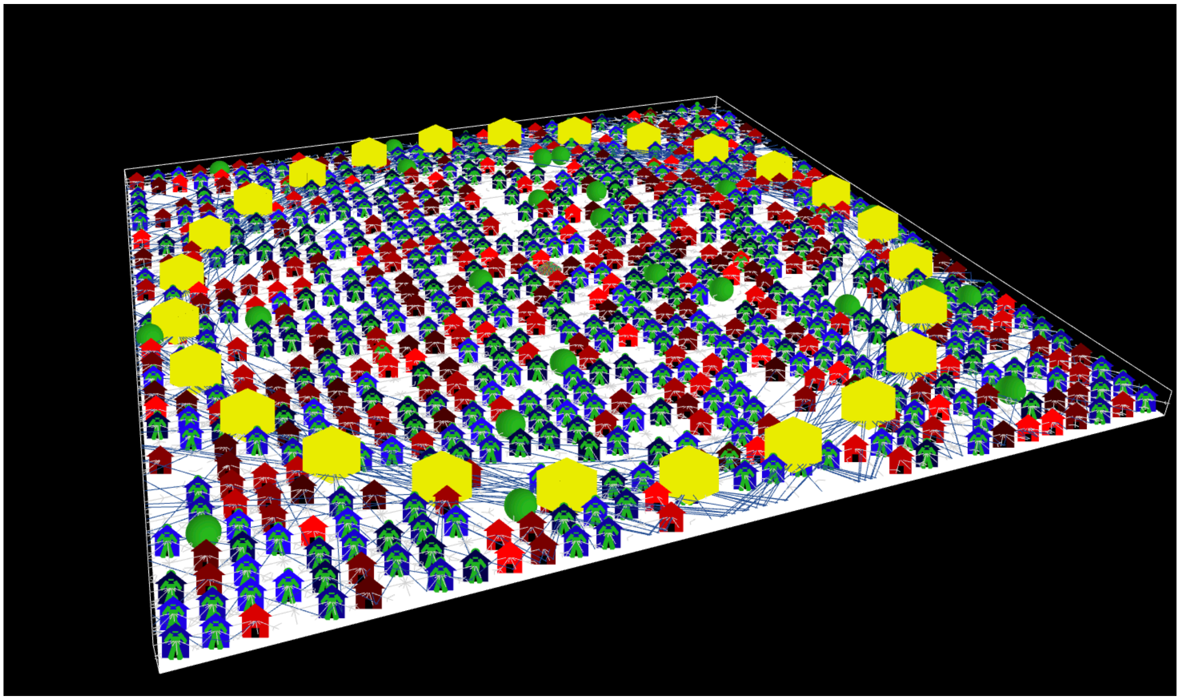

Fig. 18. Screenshot of agent-based environment with bank links incorporated to create interbank networks.

Experiment #1: Net Worth and Contagion

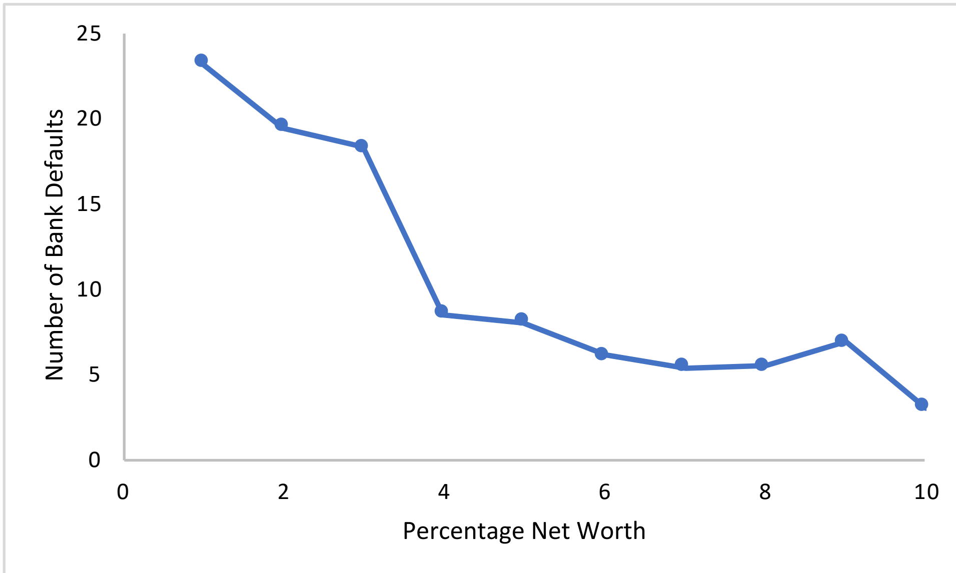

Fig. 19. Average number of defaults as a function of the capital ratio (net worth as a percentage of total assets) by running model for 50 ticks and repeating parameter combinations 10 times.

The first experiment is focused on the variation of net worth as a percentage of total assets. Figure 19 illustrates the results, which is the average of the experiment running for 50 ticks, repeated 10 times, and inclusive of percentage of net worth varying from 1-10%. Noticeably, when the percentage of net worth is low (i.e., 1-3%) a substantial portion of the banking agents default as the shock cannot be absorbed by the net worth portion of their balance sheets which is similar to findings of Nier et al. (2007).

Moreover, there is a negative relationship between bank capitalization and interbank contagion. As the net worth increases, less banks default; however, contagion does not diminish linearly as bank capitalization is increased. When net worth is valued towards the upper bound (e.g., 10%) majority of the initial shock is absorbed by the source bank. When net worth decreases, the second-round default occurs as the creditor banks become exposed and the loss is transmitted to their balance sheets. The net worth is not low enough to generate further rounds of default as net worth remains large enough to absorb the shocks. As soon as net worth is within the 1-3% range, a cascade effect takes places and a substantial amount of the banking agents default given that the net worth cannot absorb the shocks. Multiple rounds of default are experienced. The results from this experiment imply that low levels of aggregate net worth can lead to contagion within the interbank network causing multiple rounds of default due to the initial shock experienced by a source bank. Moreover, this demonstrates how the sensitivities within the percentage devoted to net worth can impact banks even if they do not experience the initial shock themselves.

Experiment #2: Interbank Lending and Borrowing and Contagion

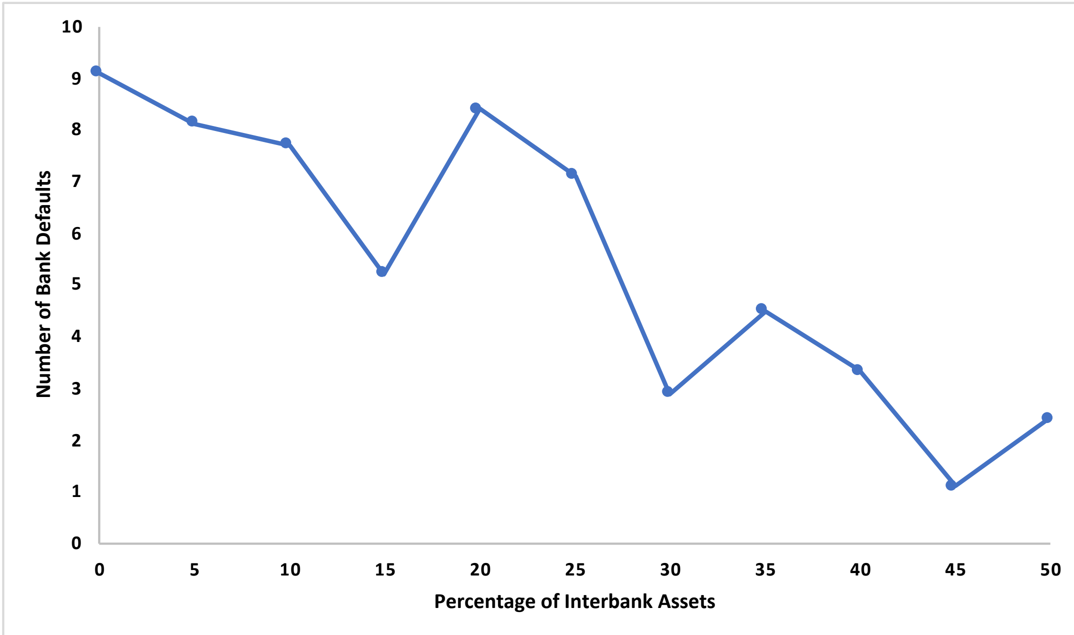

Fig. 20. Average number of defaults as a function of the percentage of interbank assets within total bank assets. by running model for 50 ticks and repeating parameter combinations 10 times.

The second experiment is focused on how the size of interbank borrowing and lending impacts the number of bank defaults. As previously mentioned, Nier et al. (2007) hold external assets constant while increasing the percentage of interbank assets; however, the model presented within this dissertation does not hold external assets constant nor at a fixed amount. The number of links is fixed given the implementation of the Erdös–Rényi construct; therefore, an increase in the percentage of interbank assets corresponds to an increase in the weight of the link (i.e., the size of the lending relationship). Additionally, net worth is calibrated as a percentage of total assets; therefore, an increase in interbank assets leads to an increase in aggregate net worth.

Figure 20 demonstrates the results for the simulation runs. As the percentage of interbank assets related to total assets increases, the number of banks that default decreases. This may be related to the notion that the transmitted losses are not large, and the overall net worth is increasing as a result of an increase in the size of the interbank market and total assets; therefore, banks are holding capital against interbank exposures. Additionally, parts of the shock are also absorbed by consumer deposits. Ultimately, this protects the banks against the contagious effects resulting from the propagated shocks. Spikes in the figure (e.g., at 20%) may be related to an increase in the transfer of the loss resulting from the shock to the creditor banks during the simulation runs. As illustrated, on average, the number of defaults does not tend to be larger than 9 banks defaulting throughout this experiment. This is related to the net worth of the source bank and the creditors absorbing a large portion of the initial shock given that interbank assets have increased for all banks, and a smaller portion is transmitted to agents in further rounds. Furthermore, this experiment demonstrates that increases in interbank assets tend to help banks absorb contagious effects as the bank holds capital against interbank exposures.

Experiment #3: Interbank Network Connectivity and Contagion

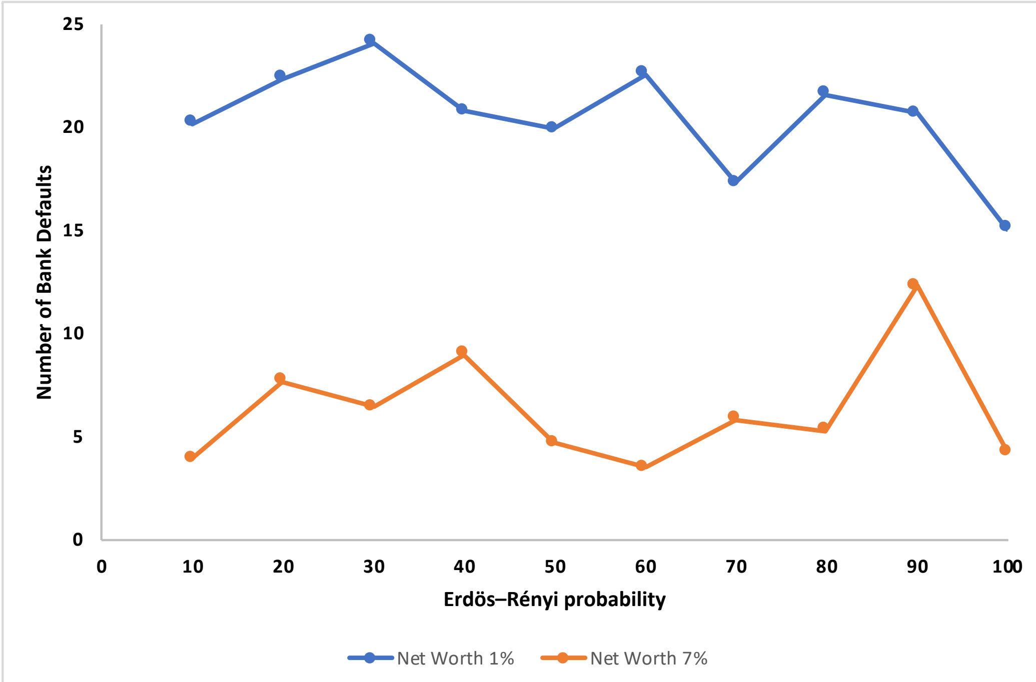

Fig. 21. Average number of defaults as a function of the probability of connectedness with respect to simultaneous variation of percentage of net worth. Includes running model for 50 ticks and repeating parameter combinations 10 times.

The third experiment focuses on the effect of connectivity on contagion within the interbank network. As a simultaneous varying parameter, I also fluctuate net worth to be 1% and 7% to illustrate how the combination influences the number of bank defaults. The horizontal (x) axis in the figure is the Erdös–Rényi probability, which implies higher levels of connectivity as the probability increases. The blue line represents an input parameter of 1% net worth and the orange line represents 7% net worth of total assets. The combination of the parameters presents an interesting insight. Increases in interbank linkage allows for shocks to be transmitted across the systems more easily; however, it also allows for shocks to be absorbed more easily by the net worth of the other banks. Figure 21 presents the results from the experimental runs and demonstrates that this concept almost leads to an M-shaped graph, which is somewhat similar to Nier et al. (2007)'s findings. When the Erdös–Rényi probability is low, there is an increase in bank defaults since the low level of connectedness may lead to transmission of the shock. When the connectivity is in between the upper and lower bound range, we see a fluctuation in the number of banks that default; however, typically as connectivity approaches the upper bound of the range, there seems to be lower levels of bank defaults as the impact from contagious effects diminishes given that the shock absorption technique begins to take place. Moreover, a larger portion of the banking population is capable of withstanding the shock.

Figure 21 also displays the interdependent relationship between connectivity and net worth. When net worth is 1% of total assets, a large portion of the banks still default as they are unable to absorb the shock through the net worth portion of their balance sheets. Moreover, the interbank linkages transmit the shocks rather than absorb it. When net worth is 7% of total assets, we still notice bank defaults but at a substantially lower rate than when net worth was 1%. Therefore, the results imply that higher levels of connectivity with low levels of aggregate banking capitalization are more inclined to suffer from contagion than systems with higher levels of connectivity and aggregate banking capitalization.

Experiment #4: Concentration of Banking System and Contagion

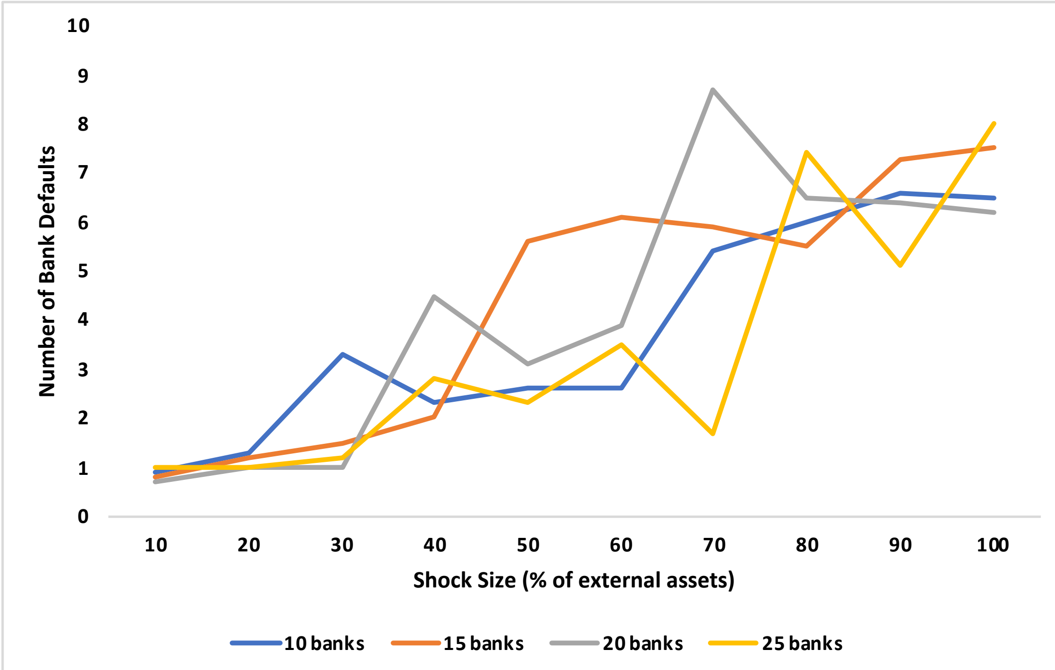

Fig. 22. Average number of defaults as a function of the size of the shock as a percentage of external assets for varied number of banks. Includes running model for 50 ticks and repeating parameter combinations 10 times.

The final experiment focuses on the effect concentration (number of banks) within the system has on contagion given the variation in interbank connections. In order to vary the concentration of the system, the number of banks ranges from 10 to 25 banks where 10 corresponds to the highest level of concentration and 25 banks corresponds to the lowest level of concentration. As a simultaneous varying parameter, the percentage of external assets calibrated to represent the shock size also varies.

Figure 22 illustrates that regardless of how concentrated the banking system is (i.e., 10 or 25 banks), as the size of the shock increases relative to the portion of external assets, the number of bank defaults also increases denoting a positive relationship. Nier et al. (2007) found that for a given shock size, there is a higher risk of contagion as the system becomes more concentrated (i.e., as the number of banks in the system decreases). Their finding is a result of maintaining a fixed level of total assets and excluding the diversification of agents and attributes that exist in the economy (e.g., people, houses, interest rates). In other words, as the number of banks decreases, the size of each bank's balance sheet is larger given that the same value of total assets is held constant. As a result, the bank is large enough to have a substantial impact on the entire system. The result presented in Figure 22 implies that is not necessarily true as external assets may vary through each simulation run depending on this aspect of a specific bank's balance sheet. This is a more realistic approach as not all banks maintain similar sized balance sheets. Moreover, higher levels of concentration may allow for more banks to absorb the shock through their balance sheets thus withstanding the contagious effects.

Chapter 5: Conclusion and Future Research

This paper shows the power of simulation as an additional approach to scientific inquiry and builds on previous agent-based models of the real estate and financial markets. With respect to the experiment focused on housing and people, the results of the scenario simulations emphasize a tremendous influence from the abilities of the Federal Reserve to control interest rates, banks to lend to each other, and consumers to make timely payments. The Fed's control over interest rates continuously demonstrated a real estate bubble bursting around 2007 regardless of how the combination of parameters differentiated. The model incorporates many complex features representing real characteristics of consumers and banks.

After I set up the full model in the baseline run that was focused on houses and people, I conducted a number of sensitivity analyses and assessed variables that influenced the probability of foreclosures. This paper demonstrates that properties entering foreclosure certainly have an impact on neighboring properties. With respect to the banking aspects of the model, I demonstrate the power of using agent-based modeling to incorporate the non-linear aspects of interbank networks. I utilized a different methodological approach by performing comparative static experiments while allowing for consumers to behave and interact as they would have in the previous simulation runs. Comparative static experiments allow for the isolation and variation of specific parameters to see how they influence the number of bank defaults during the simulation runs. Additionally, the network structure relied on the implementation of the Erdös–Rényi construct.

Future iterations of this model and experimental runs will certainly incorporate additional parameters; however, the interbank portion of this dissertation provides insight into how net worth, size of the interbank market, connectivity, and concentration of the banking system influence the number of bank defaults. These types of experiments may be useful for both banks within the private sector and central banks of countries especially given the demand to meet regulatory requirements and robust portfolio management. Financial institutions tend to place an emphasis on stress testing, sensitivity analyses, Monte Carlo simulations, etc. as part of risk management. As previously mentioned, these experiments are guided by the methodological approach of Nier et al. (2007). With respect to net worth, the findings imply that percentage net worth of assets certainly influences the level of contagion within banking systems. As the net worth percentage diminishes, the number of bank defaults increases; however, it should be noted that this is a non-linear relationship. When the percentage net worth of total assets increases, the banking system is more likely to withstand the shock to the system as it is absorbed. This is one parameter that allows us to understand systemic risk(s) within the banking system more thoroughly.

The second experiment focused on increasing the size of the interbank market by increasing the percentage of interbank assets related to total assets. In this specific experiment, the results differentiated from Nier et al. (2007). The results from this model implied that overall aggregate net worth increases as a result of an increase in the size of the interbank market and total assets. In other words, banks held capital against interbank exposures. This ultimately suggests that banking capitalization requirements may prevent banking systems from experiencing systemic breakdowns from shocks. The diversification of assets also helps. By retaining interbank assets, this may help protect banks from shocks related to a different asset type on their balance sheets.

The third experiment focused on how connectivity within the interbank market impacts contagious defaults. The results suggest that low connectivity with increases in the number of links transforms shocks into transmitters rather than absorbers. The latter, that is links act as shock absorbers, occurs when the connectivity within the network is high. I was also able to demonstrate the interdependence of this concept and bank capitalization by running the simulations with a range of net worth. As connectivity increased while the net worth percentage was low (i.e., less capitalized) there was a higher number of banks which defaults and thus were impacted by contagious defaults. Although banks still defaulted when the net worth percentage was increased, a substantially smaller portion defaulted; therefore, this demonstrated that net worth once again acts as a significant absorber of shocks.

The final experiment related to the interbank networks varied the concentration of the system and size of the initial shock. One commonality of the findings with Nier et al. (2007) relates to when the size of the shock increases, relative to the portion of external assets, the number of bank defaults also increases denoting a positive relationship. However, again, some of the findings differentiated from Nier et al. (2007) as their model does not incorporate a diverse set agents within the economy (e.g., people and varied levels of total assets). The findings from the experiment in this paper imply that higher levels of concentration may allow for more banks to absorb the shock through their balance sheets thus withstanding the contagious effects. Certainly, if the system was less concentrated and included banks with extremely large balance sheets, then perhaps the system may withstand rounds of contagious default; however, the financial markets are composed of banks from small to large and may have different impacts due to this diverse attribute.

Most importantly, this agent-based model still has plenty of features that may be included to further model the real estate and financial markets within the United States. As I continue to expand on this model, I would like to place more emphasis on adding features to represent MBS trading, sub-prime mortgages, credibility and debt-to-income ratio of borrowers, credit default swaps, quantitative-easing (another Federal Reserve tool), Dodd-Frank Act, lending standards and deregulation, etc. Additional agents will include rating agencies such as Standard & Poor (rating agency), Fannie and Freddie (government-sponsored enterprises), and construction companies to control the supply side and pricing of homes. Another necessary component for the model is the ability for borrowers to prepay and refinance mortgages. In summary, agent-based modeling is a valuable tool and can help us monitor and prevent systemic risk in the housing market, and it allows us to gain a better understanding of emergence and interconnectedness in the "world." Finally, the interbank network aspect of this dissertation demonstrates that there are numerous opportunities to experiment with topics such as liquidity risk. Also, within this model, there is the opportunity to experiment with variations of parameters and attributes related to different types of agents. For example, we can experiment with distributions of income related to people, house prices, foreclosure contagion effects, and specific aspects of balance sheets such as net worth.

The primary purpose of this dissertation was to demonstrate how we must possess a diverse set of tools when attempting to model aspects of the real world. In this case, the housing and financial markets. I am simply recommending that central and private sector banks expand their analytical tools to appropriately analyze the non-linear world we live in. The 2008 Financial Crisis was a clear demonstration of how weak risk tools, disinformation, etc. may lead to a catastrophic event that can impact the entire globe. By incorporating approaches such as agent-based modeling, we can possess one more tool to our toolbox to mitigate risk and contagion.

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Appendix

Initial Steps: Rent or Purchase Decision-Making Algorithm for a Single Property

```
If consumer is a renter
    Ask if consumer can afford to rent property
        If yes
            Rent house, relocate, and check financial status
        Else
            Exit system
    If  renter is solvent
        Ask if renter can purchase primary residence
            If yes
                Purchase primary residence
            Else
                Check financial status
    Else
        Exit System
Else
    Ask if consumer can afford to purchase primary residence
        If yes
            Purchase primary residence
        Else
                Ask if consumer can afford to rent property
        If yes
            Rent house, relocate, and check financial status
        Else
            Exit system
    If  renter is solvent
        Ask if renter can purchase primary residence
            If yes
                Purchase primary residence
            Else
                Check financial status
```