# RETHINKING HOUSING WITH AGENT-BASED MODELS: MODELS OF THE HOUSING BUBBLE AND CRASH IN THE WASHINGTON DC AREA 1997-2009

by

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A Dissertation
Submitted to the
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of
Doctor of Philosophy
Computational Social Science

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# Rethinking Housing with Agent-Based Models: Models of the Housing Bubble and Crash in the Washington DC Area 1997-2009

A Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at George Mason University

by

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## DEDICATION

I dedicate this dissertation to my wife, Stephanie, and our children.

## ACKNOWLEDGEMENTS

I thank the professors and graduate students with whom I worked on the Housing Market Model—Rob Axtell, Doyne Farmer, John Geanakoplos, Peter Howitt, Matthew Hendrey, Nathan Palmer, Ben Conlee, Chun-Yi Yang, Ernesto Carrella, and Philip Kalikman. They all contributed in some manner to the model that is the centerpiece to my dissertation. Particularly, I thank Rob and Doyne for guiding me as a researcher on the Housing Market model and other research pursuits as well as serving on my committee. Thank you also to Bill Kennedy and Carlos Ramirez for serving on my committee and providing feedback to improve the dissertation. Finally, I acknowledge my coworkers who were always respectful of the time needed to complete a PhD program.

**TABLE OF CONTENTS**

## LIST OF TABLES

## LIST OF FIGURES

## LIST OF ABBREVIATIONS

# ABSTRACT

RETHINKING HOUSING WITH AGENT-BASED MODELS: MODELS OF THE HOUSING BUBBLE AND CRASH IN THE WASHINGTON DC AREA 1997-2009

Jonathan Goldstein, Ph.D.

George Mason University, 2017

Dissertation Director: Dr. Robert L. Axtell

This dissertation presents a series of related agent-based models (ABMs) of the housing market in the Washington DC Metropolitan Statistical Area. The models investigate the causes of the housing market bubble and crash during the time period 1997-2009 and policies that could have avoided such a crisis. The work in this dissertation contributes to three research areas: understanding the underlying causes of the housing crisis, demonstrating the ability of ABMs to generate important macro phenomena, and improving ABM methodology.

Using the housing market models, I investigated counterfactual policies related to the causes of the crisis. I show that leverage and expectations are the two most prominent contributors to the bubble, but that other factors, such as interest rates, norms governing the share of income going to housing, and seller behavior all influence the bubble. I find that lending standards and refinance rules play almost no part in the bubble, contrary to some theories of the housing crisis. Towards the end of the dissertation, I pair the housing

market with a model of mortgage-backed securities. I show that the increased velocity of lending made possible by securitization can increase the size of bubbles and make markets more fragile, increasing the likelihood of crashes.

The ABMs in this dissertation exploit multiple large, heterogeneous data sets and utilize behavioral rules that are more realistic than conventional neoclassical specifications to reproduce detailed housing market dynamics. Input data include loan level data, multiple listing service (MLS) records, and demographic information from a variety of sources. The ABMs exploit this data by choosing the precise areas of input distributions to use based on the context of the model. This allows the ABMs to match not only aggregate outputs, but intermediate outputs and data distributions. For example, the ABMs in this dissertation not only reproduce empirical macro phenomena, such as the shape of the house price index, but also intermediate variables (e.g., distribution of loan types, average leverage, average days on market, average ratio of sold price to original listing price) and output distributions (e.g., distribution of house prices).

Throughout the dissertation I follow several methodological principles in construction and analysis of the ABMs. First, I demonstrate the use of data to constrain the models. Next, I describe a sensitivity analysis methodology that goes beyond parametric variations, but also varies model rules in what I term a structural sensitivity analysis. I demonstrate how criticisms about ABMs with regard to their opacity, brittleness, and dependency on arbitrary modeling decisions can be resolved through such an analysis. I also describe the architectural design of the models, which makes explicit the theoretically-inspired behavioral rules, facilitating structural sensitivity analyses.

# 1. INTRODUCTION

The real estate crash in 2007 played a pivotal role in creating the financial crisis that followed. Not only did it sharply reduce wealth for many homeowners, but the subsequent drop in value of mortgage-derived securities triggered financial cascades that harmed or bankrupted many financial institutions (Gorton 2008). The damage to the financial community eventually flowed back into the real economy through tightened lending, doubling unemployment from 5% to 10%. However, the precise causes and policy measures that could have attenuated the real estate crash in 2007 are still debated. A sample of typical causes argued focus on leverage (Geanakoplos 2010, Haughwout et al. 2011), lending standards (Duca, Muellbauer, and Murphy 2011, Mian and Sufi 2009), changes in expectations (Hott 2009, Case and Shiller 2003), adjustable rate loans (Liebowitz 2009), inflows of foreign savings (Bernanke 2009), interest rates and associated refinance (Khandani, Lo, and Merton 2009), too little regulation (Gorton et al. 2010, Pozsar et al. 2010), mortgage backed securities (Levitin and Wachter 2012), and a banking panic (Gorton 2012). Moreover, even within a particular explanation, the policy decisions that led to or which could alleviate that cause are hotly debated. For example, if the crash is pinned on excessive leverage, what role did securitization play in enabling that leverage and in transmitting the risk of that leverage to financial institutions? Sorting out the complex causality and interrelation of these phenomena requires a virtual laboratory that can be used to trace through the causal mechanisms that lead from policy decisions and other environmental factors to outcomes, such as the housing crisis. Moreover, the virtual laboratory can be used to run counterfactuals to test different policy decisions, to understand both how a particular historical event could be avoided and the likely future consequences of new policy decisions.

This dissertation describes an attempt to create such a virtual laboratory to study the housing market of the Washington DC Metropolitan Statistical Area (MSA) and explores examples of policy analyses and counterfactuals that such a laboratory enables. The powerful combination of agent-based modeling with vast amounts of empirical data enables the model outputs to closely approximate a wide variety of real characteristics of the real estate market, household balance sheets, and the mortgage market. This high degree of fidelity allows more confident policy analyses and counterfactual investigations. I show that leverage and expectations are the two most prominent contributors to the bubble, but that other factors, such as interest rates, norms governing the share of income going to housing, and seller behavior all influence the bubble. I find that lending standards and refinance rules play almost no part in the bubble, contrary to some theories of the housing crisis (e.g., Gorton 2012, Khandani, Lo, and Merton 2009). Still, the model does not match all data, and there are a number of critical elements the model lacks. Towards the end of the dissertation, I describe an offshoot model that adds the interaction of mortgage-backed securities with the housing market. Such an extension could increase the potency of the base model. I show that the increased velocity of lending made possible by securitization can increase the size of bubbles and make markets more fragile, increasing the likelihood of crashes.

The dissertation is organized as follows. This chapter overviews the problem and related work and compares the approach I take with conventional housing and mortgage models. The next chapter describes the data used in the model. Chapter 3 overviews the base model's architecture, providing pseudo-code, equations, narrative descriptions, and diagrams. Chapter 4 presents the model's typical outputs and demonstrates how to use the model to explore potential policy alternatives. This dissertation uses three different versions of the house market model. In Chapters 3 and 4, the version of the model I helped design and code is studied. In Chapter 5 I move to the most recent version of the model and perform a sensitivity analysis on the model's rules and parameters. I briefly describe the model's upgrades—done by other researchers (see Axtell et al 2014)—before diving into the analysis. Chapter 6 moves to a separate extension model in which I couple a mortgage-backed securities market with a housing market model similar to the base model described in this dissertation. Chapter 7 concludes and suggests avenues for future research.

## 1.1. Related Work

There is an extensive literature describing the origins of the housing bubble and crash. Important in many of these analyses is the effect of leverage in the housing market. In housing, leverage is described by the loan to value (LTV) ratio, which measures the ratio of the outstanding principal on loans for a particular house to the house's fair market value. Often this ratio is multiplied by 100, and an LTV above 100 is considered "underwater" since the debt on the house is a higher than the house's value. Archer and Smith (2010) list underwater mortgages as a leading cause of mortgage default during the housing crash.

More broadly Geanakoplos (2010) describes the "leverage cycle" and applies it to explain the housing market gyrations in the 2000s. Leverage cycle theory posits that the most optimistic buyers of an asset drive prices up during boom times. These traders become heavily leveraged in order to buy the asset, and as long as the asset's price is rising, they will gain wealth and further drive the asset price up. Once the market turns—due to "scary bad news" that increases uncertainty and leads to tighter lending standards—the asset's price starts falling and the optimistic traders lose wealth. The asset falls more and more into the hands of pessimistic traders further driving down its price. The cycle, which Geanakoplos terms the leverage cycle, exacerbates price cycles in assets. The leverage cycle mechanism in which asset booms become inherently unstable due to excess leverage is similar in theme to Minsky (1986).

Many homeowners took out high LTV loans during the height of the housing market price run-up; similarly, many investors became highly levered in asset-backed securities. When the market peaked and started declining, these investors sustained losses and the houses and mortgage-backed securities fell to others who valued them less (or were more risk averse). In an analysis of the housing market during the crisis, Haughwout et al. 2011 found evidence in support of the leverage cycle—specifically, "flippers" who bought, fixed up, and quickly sold houses played the part of highly levered optimistic buyers who drove prices during the house price run-up and sustained huge losses during its crash. On the other hand, not all authors agree that leverage was the primary factor in the housing bubble and crash. Glaeser, Gottlieb, and Gyourko (2012) found that neither interest rates, loan approval rates, nor downpayment requirements—which is directly related to leverage—could explain the housing bubble. On the other hand, Duca et al. (2011) argue leverage was an important factor in the housing bubble.

Khandani et al. (2009) describe a concrete mechanism that leads to increased leverage, involving the interplay of declining interest rates, appreciating house values, and the opportunity to refinance. The authors argue these three factors lead to systemic increases in leverage in the housing market due to massive equity extraction through cash-out refinancing of mortgages. They describe the "refinance ratchet" in which low interest rates incentivize households to refinance repeatedly. Rather than paying off mortgages, households extract equity through the refinance process increasing overall debt and leverage as house prices appreciate. Importantly, widespread refinance coordinates loan origination so that households who bought houses at different times have loans originations from the same time period. On the flip side, homeowners cannot incrementally deleverage by selling a portion of their house when house price appreciation ceases. When prices decline enough, historically uncorrelated defaults become more highly correlated since many households own loans originated at the peak of the market.

Other analyses focus less on leverage and more on the quality of loans issued during the housing bubble. Mian and Sufi (2009) argue that the housing bubble was caused by expansion of credit to less credit-worthy borrowers ("subprime" borrowers) leading to an increase in housing demand that drove up prices. At the same time, this increase in demand came from the riskiest borrowers also increasing the riskiness of mortgage-backed securities. This is essentially the argument from Duca et al. (2011) who pair weakening credit standards with innovations in mortgage backed securities (MBS), such as traunching and credit default swaps, as primary in both the bubble and crash.

It is difficult to decouple the housing bubble and crash from the financial crisis in general. Pozsar, Adrian, Ashcraft, and Boesky (2010) describe the "shadow" or "parallel" banking system and how it operates in relation to the housing market. This system ultimately governs the supply side of the loan market since most mortgages are not held by lenders but rather placed into mortgage pools on whose cash flow claims are sold to investors. These claims, called residential mortgage-backed securities (RMBS) play a central role in many discussions of the financial crisis. The "originate to distribute" hypothesis blames the practice of banks securitizing mortgage loans and selling these securities to investors (Bord and Santos 2012). This practice lowered banks' incentives to price loan risk because banks no longer bore most of this risk. Furthermore, investors who bought the securities were too far removed from the loan origination to price the risk (see e.g., Ashcraft and Schuman 2008 who list this and other incentive problems with subprime origination, such as the principal agent problem between investors and asset managers). "Originate to distribute" explains some of the observations (e.g., from Mian and Sufi 2009) that credit standards declined during the house price bubble. Gorton (2008) provides a counter argument, suggesting the causality is reversed—securitization did not lower credit standards, but rather lower credit standards were a problem for securitization. He argues that in other markets, securitization did not cause the same subprime lending as housing. Rather, subprime loans were given to borrowers on terms that were too onerous for borrowers in the absence of house price appreciation and refinancing (when teaser rates on adjustable rate mortgages expired). When house prices stopped appreciating, people started defaulting. When it was revealed to investors through futures indices that it was common knowledge that everyone thought subprime loans were poor investments, a run on securities that might be backed by subprime loans ensued. Similar to Khandani et al. (2009), Gorton places refinance and house price appreciation as central to the housing crash. However, analysis is this dissertation finds refinance not to play an important role in the crisis. Chapter 6 of this dissertation considers an extension to the housing market models of Chapters 3-5, coupling the housing market to the RMBS market.

Undoubtedly, there are other factors that influenced the housing market gyrations in the 2000s. For example, Bernanke (2009) argues that a huge amount of capital influx—the "global savings glut"—poured into the secondary mortgage market. Global investors were searching for safe, high return assets and invested in MBS, which drove up demand for mortgages and thus weakened credit standards, also reducing the real interest rate. Other authors discuss the role of heterogeneity and expectations. For example, Geanokoplos (2010)'s leverage cycle is driven by a heterogeneity of asset valuations. Case and Shiller (2003) describe "irrational exuberance" in the housing market as leading to the housing bubble. Hott (2009) also relies on changing agent expectations to explain house price fluctuations.

In building an agent-based model to capture many of these insights, there are a number of sources from which to draw insight. Axtell's (1999) firms model is one of the earliest compelling agent-based models in which he showed simple rules could produce many more empirical regularities of firm populations than most mathematical models. Delli Gatti et al. (2011) created agent-based models directly relevant to conventional macroeconomic analysis. The authors model the interactions between firms, banks, and individuals and are able to produce business cycles, typified by sustainable growth, followed by leveraged growth, followed by bankruptcies, and finally a consolidation of positions. Ashraf et al. (2011) also build an agent-based macroeconomic model, which focuses more on individuals (i.e., in starting firms and supply heterogeneous skills) rather than business cycles. There are many agent-based models of financial markets, such as Lux (1998), LeBaron (2001), and Alfarano and Lux (2007) to name a few. These models typically contain agents that price a risky security using some heuristic procedure, such as reinforcement or imitative learning. Additionally, there have been a few agent-based housing market models already published. A previous paper on this housing market model has been published (Geanakoplos et al. 2012), and this dissertation expands on that paper. Gilbert, Hawksworth, and Swinney (2008) constructed a qualitative model of the UK housing market, but did not attempt to calibrate the model to empirical data.

## 1.2. Agent-Based Modeling versus Conventional Modeling

Agent-based models (ABMs) are computational models in which individual agents interact directly with each other and their environment, rather than through aggregate equations. ABMs focus on the individual elements (agents) of a system and their relationships, encoding specific behaviors and agent goals that model the deep structural properties of the system. When environmental conditions change, agents' behaviors change in the model, often leading to cascades in which changes to one agent's behavior further alters the behavior of another. At the system level, these individual changes and cascades cause nonlinear responses of the system to stimuli, often termed "unanticipated behaviors" or "emergent properties." ABMs are bottom up models that focus on micro fundamentals and interactions to derive system level properties.

ABMs differ from traditional approaches to economic modeling, which are typically mathematical models involving one or a few representative agents solved for equilibrium rather than simulated (Mas-Colell, Whinston, and Green 1995). These analytic models are more parsimonious than ABMs and have provable properties. Often their parsimony allows them to be communicated more easily in the space of a journal article than an ABM. By contrast, since ABMs are simulated rather than solved, they are unconstrained by analytical tractability. ABMs can handle heterogeneity, boundedly-rational behavior, and individual interactions, and ABMs can utilize empirical data better than mathematical models.

Housing markets are a particularly appropriate area for ABM application. These markets involve complex interactions, massive heterogeneity, and market frictions.

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. Heterogeneity comes not only in the form of differing wealth and income, but also in preferences, expectations, and risk tolerance. Market frictions include scarcity of information (typically buyers can only look at a few houses per week), large transaction costs, and the indivisibility of houses. Whereas traditional mathematical economic models, such as dynamic stochastic general equilibrium (DSGE), can incorporate some of these complexities it becomes computationally infeasible to include more than one or two. On the other hand, since ABMs are encoded in an object oriented programming language and then simulated, it is natural to include these various complexities and frictions into a model.

The main criticisms of ABMs are that they are ad hoc and opaque. ABMs permit flexibility in model creation, and this flexibility enables modelers to build almost any type of model. Traditionally, ABMs have lacked discipline. By contrast DSGE models are disciplined by the requirement for agents to be rational, and the system to remain in (or quickly return to) equilibrium. The housing market ABM described in this dissertation describes a different type of disciple, more applicable to ABMs: coherence to empirical data. The housing market ABM uses empirical data on housing market behavior (from the Washington DC Multiple Listing Service), loan characteristics (from LoanPerformance), agent attributes (from Internal Revenue Service and the Panel Study of Income Dynamics), and housing characteristics (from Housing Vacancy Survey). Later, I show that the housing market model matches many empirical outputs, not just price and quantity but also intermediate outputs, such as time on market, inventory, leverage, loan type, and others. Moreover, the outputs match in distribution as well as average. The next chapter dives more deeply into this data, and the chapter that follows describes how the housing market ABM exploits that data.

## 2. DATA

A significant advantage of agent-based models (ABMs) is their ability to ingest heterogeneous micro-data. This chapter discusses the housing market model's input data sources. Table 1 describes the data sources used in the Housing Market Model, both for input data as well as the output data used to test the model's correctness.

**Table 1 Description of Empirical Data used in Housing Market Model**

| Data Source | Description | Purpose |
|---|---|---|
| **S & P Case Shiller Index (Seasonally Adjusted)** | Index of historical house prices | Provides summary output target (not used in execution) |
| **LoanPerformance** | Detailed monthly data on loans, mostly non-agency loans | Used to derive agent probabilities for default, LTV, refinance, loan type, and rate |
| **Multiple Listing Service (MLS)** | Detailed records of real estate listings and transactions | Parameterize seller ask price algorithm and provides output targets (e.g., time on market) |
| **CoreLogic** | Provider of aggregate and loan-level data for ~85% of loans in the DC MSA | Historical data comparisons (delinquenices, foreclosures); also replaced LoanPerformance data in later model versions. |
| **Internal Revenue Service (IRS)** | Data on household demographics and income | Calibrate income distribution and sets number of households in simulation |
| **Housing Vacancy Survey (HVS)** | Data on home ownership rate and vacancy rate | Provides output targets (vacancy and homeownership rate) |
| **Panel Study on Income Dynamics (PSID)** | Income and wealth data | Calibrate income adjustment process and wealth distribution |
| **Freddie Mac** | Aggregate rate data | Historical mortgage prime rates |

Most of this data is specific to the DC MSA, including the two key data sets—the loan level data and real estate market data. The one data source not exclusive to the DC MSA was the Panel Study on Income Dynamics (PSID) data, from which we computed the liquid wealth distribution of households and calibrated the income adjustment process. There was no available PSID data restricted to the DC MSA so we used the national data.

Before describing the input data, it is useful to first look at the key aggregate output to which I compare the model output, the Case-Shiller index. This index summarizes the housing market and provides context to the data discussion in the rest of this chapter. The Case Shiller index (see [http://www.corelogic.com/products/corelogic-case-shiller.aspx](http://www.corelogic.com/products/corelogic-case-shiller.aspx)) measures house price appreciation using repeat sales. To get a feel for the methodology, I review here how the housing market model computes its own endogenous house price index using a simplified version of the Case-Shiller methodology. Specifically, the house price index computed in the model for month *m* is

$$HPI(m) = \frac{1}{|H_m|} \sum_{h \in H_m} \frac{P_h(m)}{P_h(m_h{}')} HPI(m_h{}') \tag{1}$$

$H_m$ is the set of houses sold in month *m*, and $m_h$’ is the month house *h* was most recently sold prior to *m*. For example, if a house sells for $100K in January 2000 and $150K in January 2009, this represents a 1.5 times increase in repeat sale price. The house price calculation would include an observation for January 2009 of 1.5 times the house price index in January 2000. The house price index is a useful aggregate measure of house prices and provides a quick diagnostic on model execution. Figure 1 plots the empirical (seasonally adjusted) Case-Shiller index from 1997 to 2009. The index is calibrated so that the January 2000 value equals 100. The DC area experienced a massive run-up in prices in the early 2000s, and by the peak in March 2006 the index equaled 252.4. This represents a price increase for the same house of over 150% in a little over six years. When the bubble burst, DC's crash was large but muted compared to some of the harder hit areas of the country, such as Las Vegas and Miami. The index bottomed out around 170 in April 2009.

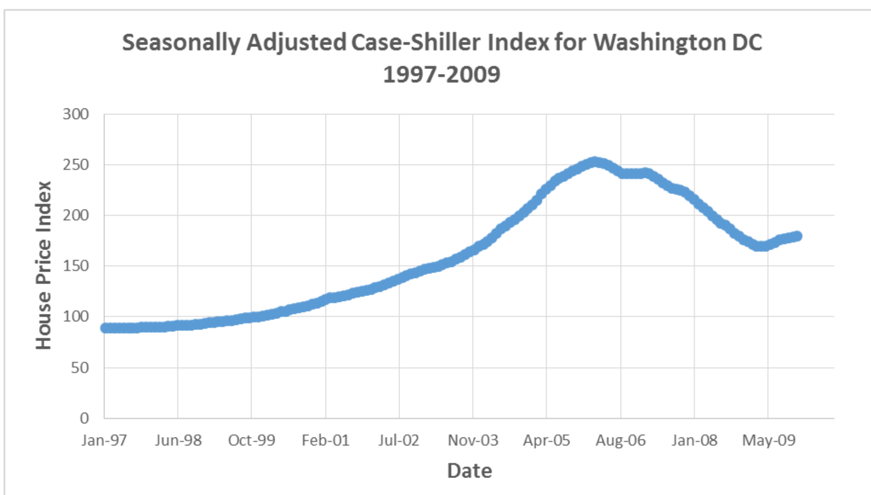



**Figure 1 Case-Shiller Index for Washington DC 1997 – 2009. Data provided by CoreLogic.**

The rest of this chapter focuses on three key input data categories: loan level data, real estate market data, and demographic data. Most of this data is used to calibrate and parameterize the model. Chapter 3, which describes the actual model logic and output, delves deeper into the output targets.

## 2.1. Loan Level Data

Particularly important to the model is the loan level data[1]. This data contains detailed information on individual loans, such as initial loan size, purchase price of house, buyer characteristics such as income and prior debt load, and monthly updates to the loans. Using this data, we can monitor how leverage changes in the economy and also calibrate behavioral rules for real estate actions such as refinance and default. Earlier versions of the model—including the one discussed in Chapter 3 of this Dissertation—used LoanPerformance data, which is particularly thorough on subprime loans, but contains few prime loans. The team attempted to rebalance the LoanPerformance data by overweighting the prime loans based on the known breakdown of prime and subprime loans for the DC MSA in each year. Later versions of the model—including the one analyzed in Chapter 5 of this Dissertation—instead used CoreLogic data whose loan coverage is better (covering 80-90% of loans in the DC MSA). Because I was less involved in the creation of the Chapter 5 version of the model, the data analysis in this chapter uses the rebalanced LoanPerformance data. Note that our model does not directly ingest individual loan data, but rather distributions derived from the individual loan data.

[1] Note that in neither CoreLogic nor the LoanPerformance data sets were loans matched to actual addresses nor did we attempt to do so. In the LoanPerformance case, the data was provided through a 3rd party in aggregated form. In the CoreLogic case, the team produced distributional data from the individual data, and the model works with this distributional data.

Figure 2 describes the amount of leverage house purchasers in the DC MSA acquired in 1998 via new mortgages as expressed in the re-weighted LoanPerformance data. The horizontal axis divides households by house purchase price brackets at roughly \$25,000 intervals (with larger brackets near the extremes); the depth axis divides LTV at origination by 5 percentage point intervals (with larger intervals for the less common low LTV brackets); and the vertical axis indicates the fraction of all new loan originations in 1998 that fall in a particular income bracket at a particular LTV. The chart shows that in 1998, the modal LTV bracket is the 87.5 – 92.5 bin, and there were only a few loans above 97.5 LTV.

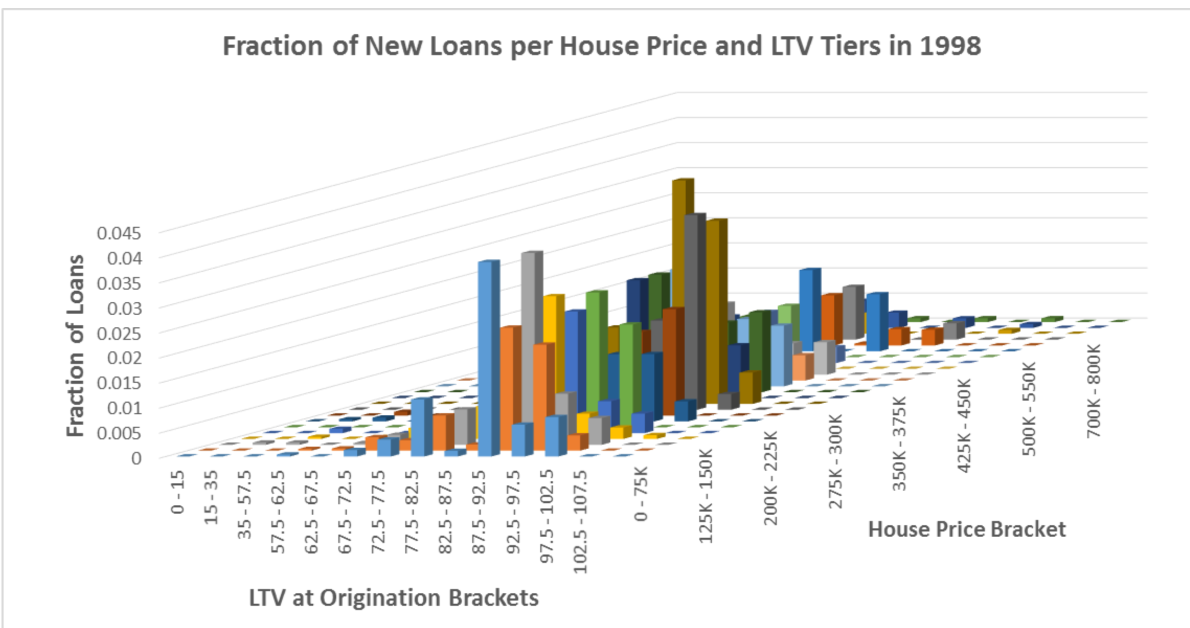



**Figure 2 Histogram of the fraction of all new loans in 1998 that fall into each purchase price and leverage bracket. Distribution derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

The housing market ABM uses this information in a straightforward manner. When a prospective buyer in the simulation attempts to acquire a loan, the buyer chooses an LTV probabilistically based on the empirical distribution of LTVs actually received by buyers who had similarly sized home purchases in the year that maps to the simulation's current run time[2]. Later, we can run counterfactuals to understand how the market would change if the distribution of LTVs handed to buyers was different. Chapter 3 provides more detail on the simulation design.

Figure 3 plots the fraction of new loans in 1998 at each LTV bracket irrespective of house price. The plot shows two peaks: one around 90 LTV and the other around 80 LTV. Note that an LTV of 80 or lower is required to obtain a prime loan and to avoid paying mortgage insurance, which explains why there is a large fraction of loans right at that threshold. The second peak around 90 LTV might represent households with a primary loan at 80 LTV and a secondary loan at 10 LTV (note our data reports combined LTV of all loans for a new house), which is a strategy households can employ to reduce interest rate and mortgage insurance requirements for some of the combined loan.

[2] Note that there are some additional difficulties because prospective buyers typically acquire pre-approval for a loan before a house purchase, but not all pre-approved buyers actually buy houses. The data presented here are for loans actually given to buyers, whereas in the model we use this distribution for the pre-approval process. The pre-approved prospective buyers who fail to purchase a house have on average a lower pre-approved LTV than successful buyers. For example, consider a household with $40,000 saved for a downpayment. With an LTV 80, the household can buy up to a $200,000 house, but with LTV of 90, the household can buy up to a $400,000. The household with a pre-approved LTV of 80 is less likely to successfully find a house, and this introduces a bias into the data distribution. To counteract this, I measured the actual bias introduced in a typical model run and adjusted the input to data to correct this bias.

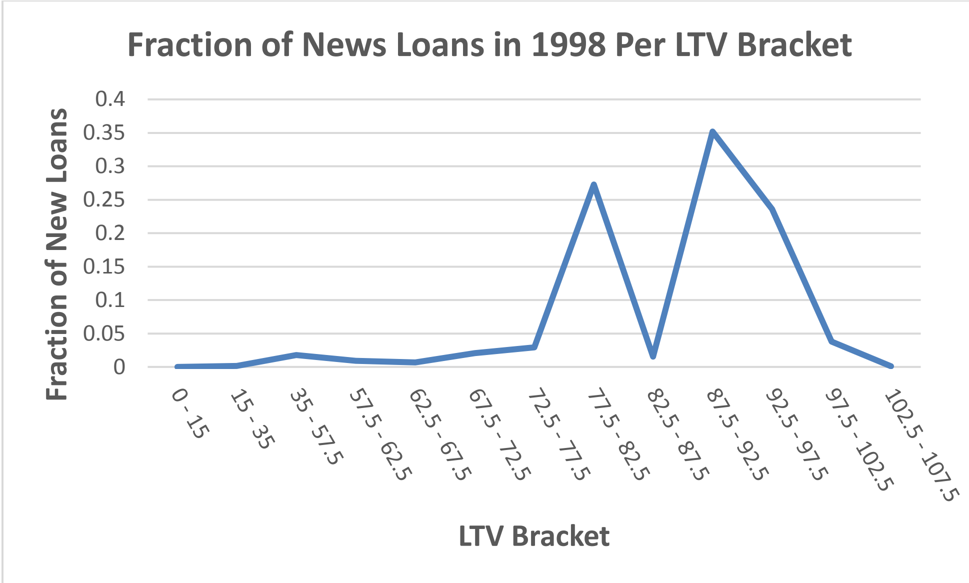



**Figure 3 Fraction of new loans in 1998 at each LTV bracket. Graph derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

Figure 4 shows the average LTV of new loans in 1998 for each purchase price bracket. Because we received the LoanPerformance data binned in the brackets from Figure 2—e.g., house price generally in $25,000 increments and LTV in 5 point increments—I computed the average LTV assuming each loan's LTV to be the center of its bin. For purchase price below $300,000, there is not much of a correlation between purchase price and LTV, but as price increases beyond $300,000, LTV is negatively correlated with price. This negative correlation is intuitive because marginal utility decreases as house value increases, and at some point it becomes more desirable to reduce debt than purchase a better house. Because I received the LoanPerformance data binned by LTV and house price—not individual loan data—I could not compute a precise correlation.

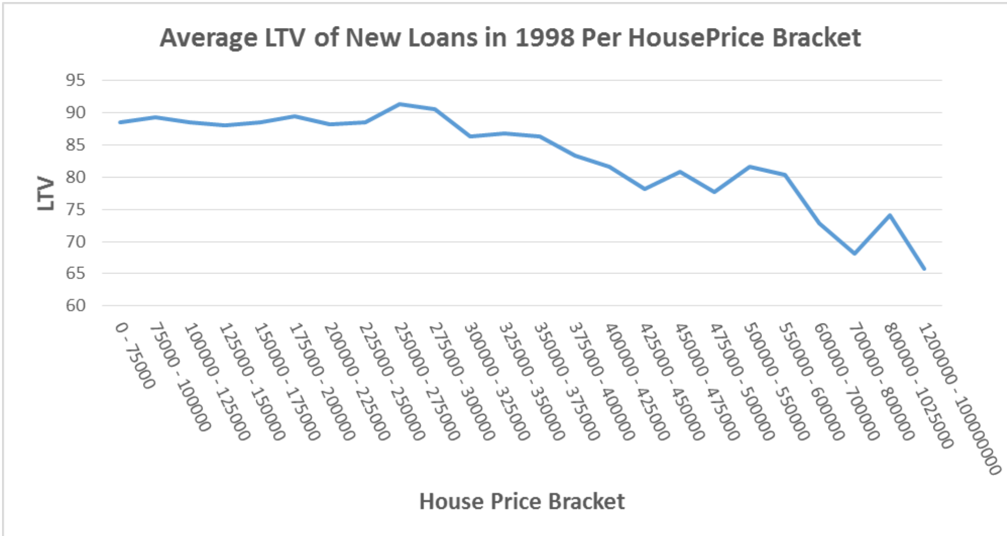



**Figure 4 Average LTV of new loans in 1998 at each purchase price bracket. Graph derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

I repeat this analysis for 2005 during the height of the bubble. Figure 5 displays the distribution of loans by LTV and house price. Here, we see that LTVs are much higher and also a larger proportion of the loans go to more expensive houses than in 1998—not surprising given the general rise in prices. The increase in leverage, including for more expensive homes, provides support to theories that pin leverage as the key factor in the housing bubble and crash. Chapter 3 tests this theory in light of other possibilities.

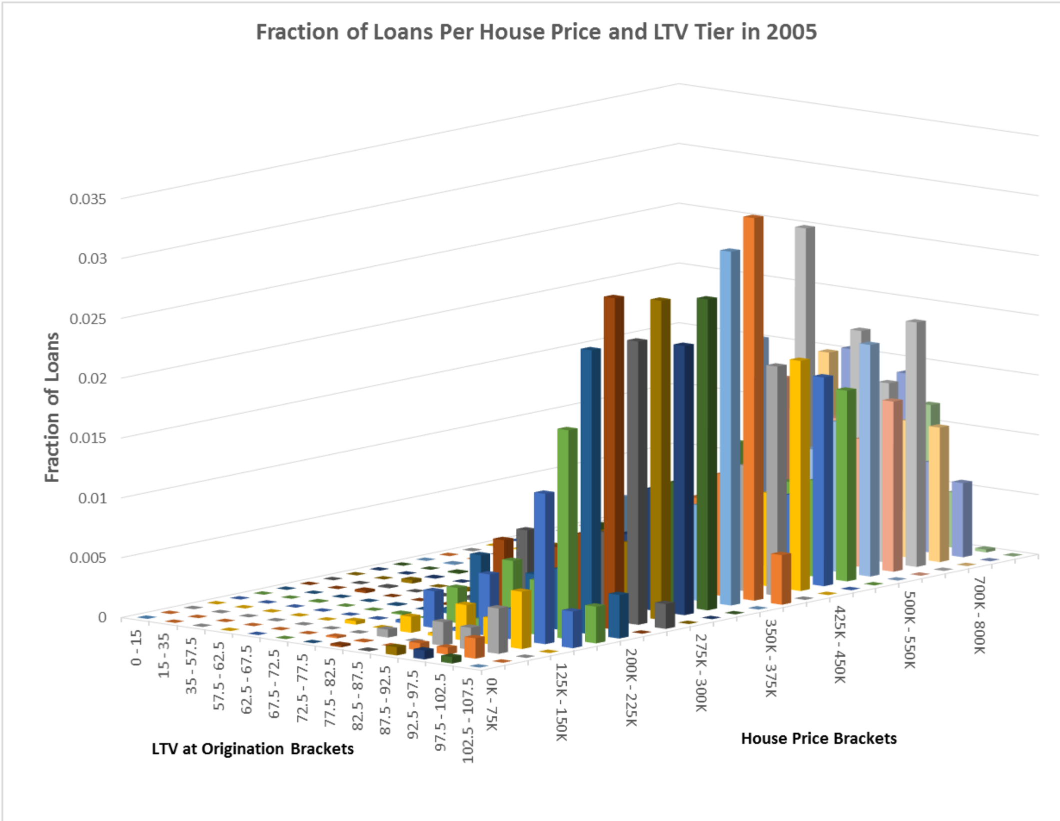
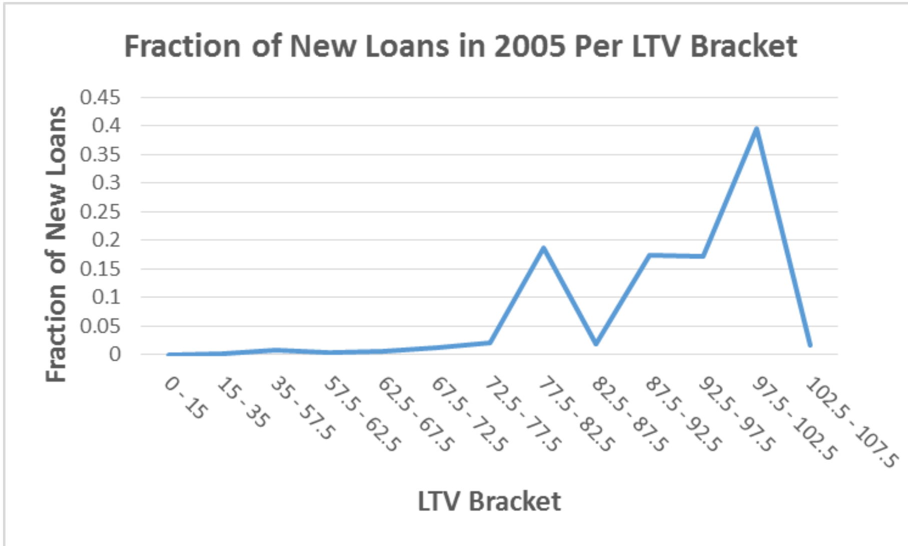
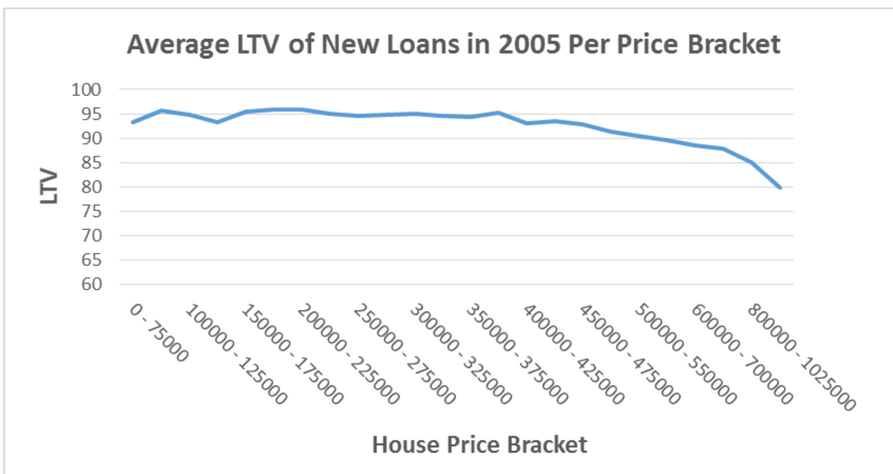



**Figure 5 Histogram of the fraction of all new loans in 1998 that fall into each house price and leverage bracket. Distribution derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

Figure 6 reinforces the observation that leverage for new loans increased between 1998 and 2005. Figure 6(a) shows that the modal LTV bracket for new loans is 97.5 – 102.5 bracket. Banks made about 40% of loans requiring close to or no downpayment. Figure 6(b) shows a similar relationship between house price and LTV in 2005 as Figure 4 showed for 1998—uncorrelated at lower prices and then negatively correlated at higher prices. However, in 2005 LTV is generally higher for all house prices and the negative correlation begins at a higher price (around $400,000 in 2005 versus $300,000 in 1998).



(a)



(b)

**Figure 6 (a) Fraction of new loans in 2005 at each LTV bracket and (b) Average LTV of new loans in 2005 at each house price bracket. Graphs derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

Finally, to summarize the leverage story, Figure 7 describes how LTV for new loans changed from 1997 to 2009—the period in which the housing market ABM was run. In 1997, average LTV was around 86, whereas by 2006 that number had risen to 93. Similarly, if we look just at the top 50% and top 35% highest LTV loans, the increase is even greater. For example, by 2005, the entire top 35% highest LTV loans were made at 100 LTV, whereas in 1997 the average for this group was 94. Interestingly, leverage declined only modestly after the crash and remained much higher in 2007 than the late 1990s.

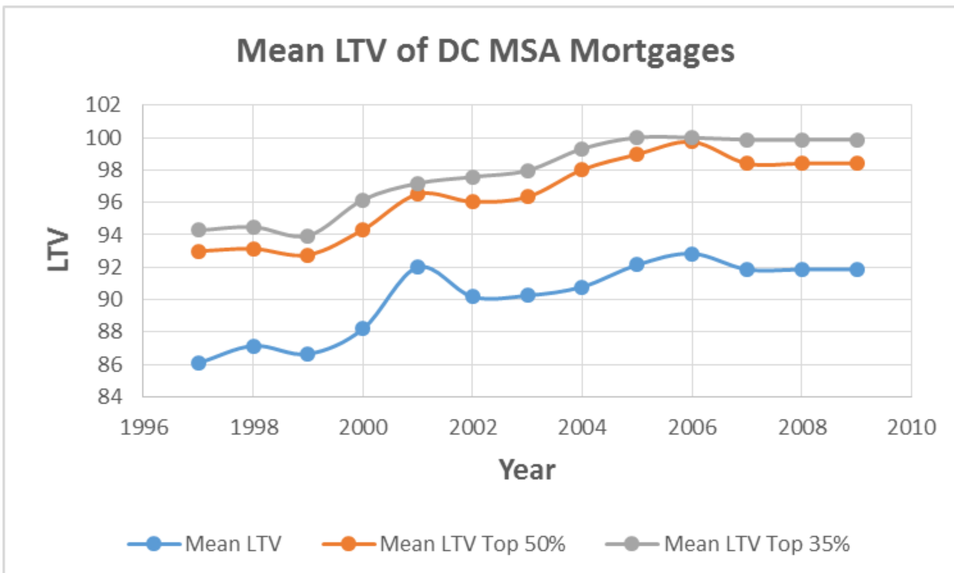



**Figure 7 Mean LTV of new mortgage loans from 1997 to 2009. Graph derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

In addition to leverage, another key burden mortgages place on homeowners is debt-service, which is the required monthly payment on loans. Debt-service is often characterized with respect to monthly income by the debt-to-income ratio (DTI). Similar to the detailed leverage data from LoanPerformance and CoreLogic, we also have detailed data on DTI. Figure 8 plots how DTI changed from 1997 to 2007. DTI actually dropped in the early 2000s before rising sharply around the height of the bubble (2003 – 2005). After 2005, DTI leveled off, but did not decrease or return to pre-bubble levels.

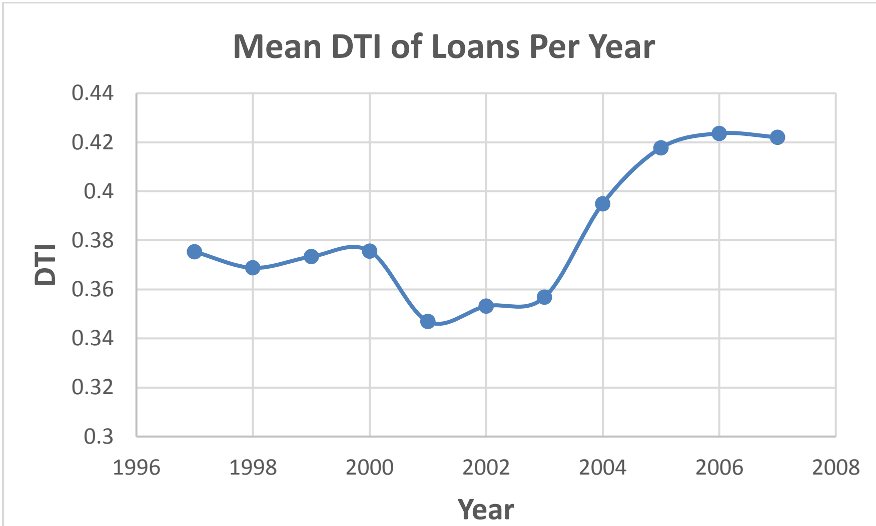


**Figure 8 Mean Debt to Income Ratio of Loans per Year. Graph derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

Changes in DTI can be due to changes in income, loan size, and interest rates. During the period of steep DTI climb from 2003 to 2005, income generally rose in the DC MSA (income discussion later in this chapter) so this would not account for the rise in DTI. Figure 9 describes how interest rates changed from 1997 to 2007. The prime rate (i.e., the rate at which prime loans to the best purchasers are lent) drops over three percentage points from May 2000 to June 2003 with half of that drop occurring in less than a year. In addition to the drop in prime rate, the average loan spread, which is the difference between a loan's interest rate and the prime rate increases in this period. This might be due to innovation in mortgage products with low teaser rates allowing those borrowers who would have typically gotten a high interest loan to acquire a loan for a lower rate. Of course once the teaser rate ends, the rate typically jumps dramatically.

However, as long as a household has home equity, it can refinance back into new loan with a low teaser rate. The drop of over four percentage in average mortgage rate from 2000 to 2003 might account for the drop in average DTI during this period.

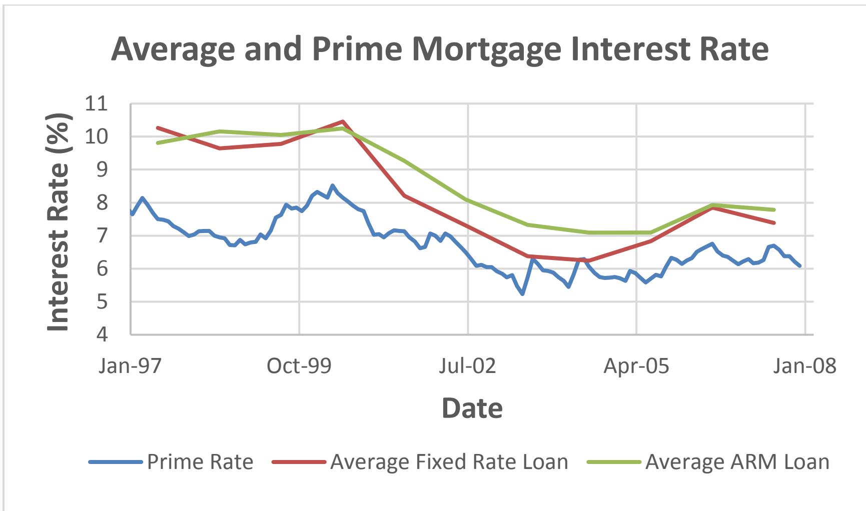



**Figure 9 Average and prime mortgage rates over time. Graph derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

Adjustable rate mortgage (ARM) loans are a key aspect of some theories of the housing crisis (e.g., Khandani et al. 2009, Gorton 2008). Figure 10 describes the fraction of all mortgage loans in the DC MSA that were ARM loans. These loans spike near the height of the bubble. Since ARM loans have an initial teaser rate, households have an incentive to refinance once the teaser period expires. Often while refinancing, a household cashes out equity accrued through increase in house value, ensuring the household remains highly levered. Once house prices fall, this highly levered household might have a loan to value (LTV) above 1.0—i.e., the household is underwater on its loan—so can no longer refinance. If the household purchased its house assuming a refinance at the end of the teaser period, the household becomes stuck with negative equity and a high interest rate. This process leads to defaults, foreclosures, and further declines in the housing market, increasing LTV for other households, which might find themselves in this same situation. Although this theory is likely part of the story, model excursions I conducted found that restricting loans to only fixed rate loans did not remove the bubble and crash. Chapter 3 describes these excursions in more detail.

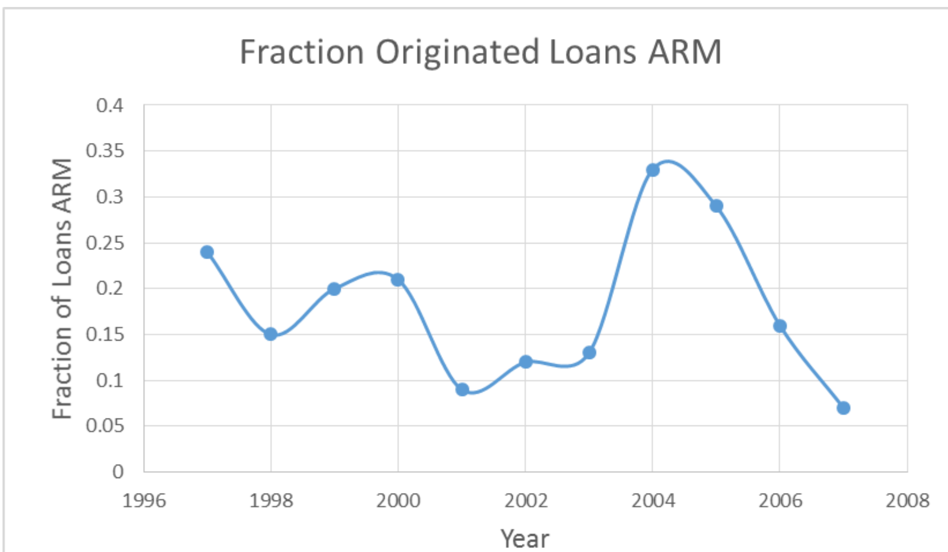



**Figure 10 Fraction of loan originations that are adjustable rate (includes both interest-only and more typical ARM loans). Graph derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

The loan data not only contains new originations but tracks loans over time. One way to characterize this is with a state transition model (Figure 11). All loans begin in the current state—i.e., the household has made all required payments. From this state, the household could fall behind (become delinquent), sell, or refinance. From the delinquent state, a household can sell or refinance their house or fall far enough behind to go into foreclosure. Alternatively, the household can catch back up to current. From foreclosure, the only next step is default. The three terminal states for a loan are home sale, refinance, and default. Month by month loan data can give insight into the transition probabilities that lead to the terminal states

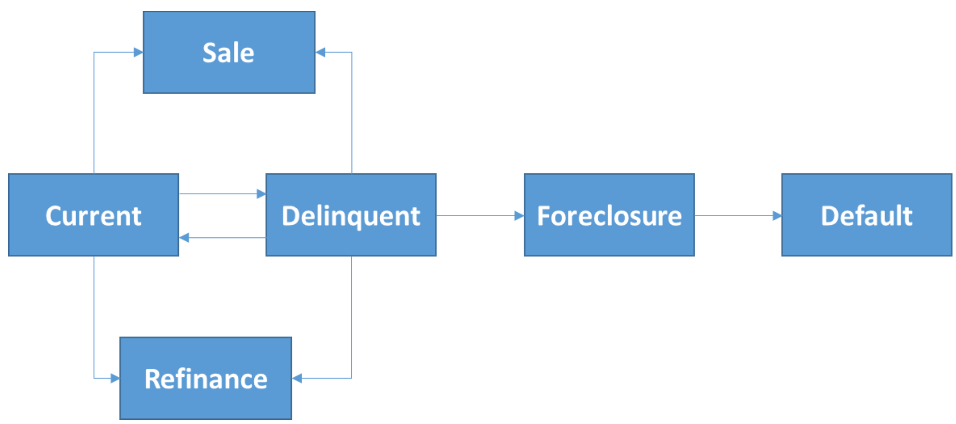



**Figure 11 Simple Loan Transition Model**

For example, one terminal loan state is default. Archer and Smith (2010) analyze defaults and give the two leading causes as a high (greater than one) loan to value ratio and a high ratio of monthly mortgage payment to income.  If a household's LTV is above 1.0, the household owes more money on its loan than the value of the house, which can lead a household to "strategically" default even if the household has the income or wealth to pay its mortgage. For example, if the household sells the house, it will have to chip in liquid wealth to pay off the loan, not to mention the transaction costs of the sale. Using data from LoanPerformance on month to month activity on loans, we estimated the probability that given a particular LTV a household would default. For example, we took all loan months in which a loan had a current LTV between 90 and 100 and found that in fraction 0.010876 of the cases, the loan transitioned from current to delinquent and never returned to current before ending in foreclosure. Note that using current LTV, not LTV at origination is important because LTV can change over the course of a loan both from paying down the loan and from fluctuations in house value. During the crash, from 2006 to 2009 average DC house price dropped by about a third, which would raise LTVs by 50% (if we keep outstanding loan principal constant). Figure 12 provides the probability of default conditional on LTV for all loans in our DC MSA sample. Of course, this does not truly measure strategic default because we do not know which defaults were strategic decisions; however, the data does show the likelihood of default increases with LTV.

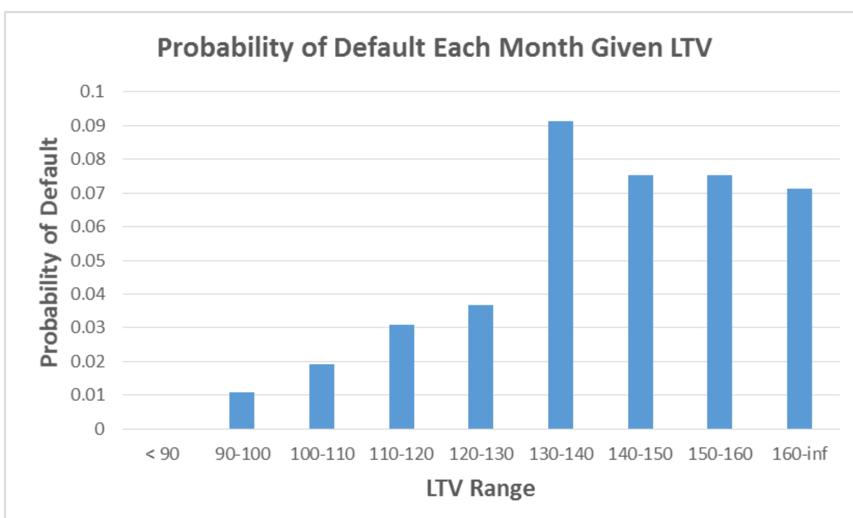



**Figure 12 Empirically derived probability of strategic default each month given LTV. Graph derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

Refinance is a second terminal state for loans. There are three main reasons households refinance: to obtain a lower interest rate, to convert home equity into liquid wealth, and to increase loan term (which, similar to obtaining a lower rate, reduces monthly payments). "Cash out" refinance is a term for refinances in which the new loan has a higher principal that the old loan. The difference in principal allows households to "cash out" part of their home equity. During years of house price appreciation, homeowners accrue illiquid home equity due to rise in house prices, and cash out refinance is a method to extract this equity into liquid wealth. Of course cash out refinance increases LTV. Figure 13, reproduced from Chen, Missoux, and Roussanov (2013), shows the fraction of refinances with equity extractions. Note this data is national, and our DC MSA loan data does not link the previous and new loan in a refinance so we cannot use this data to derive a DC MSA specific chart. Figure 13 shows that during the pre-crash years about 80% of refinances nationally involved equity extraction, and this number drops to about 20% by 2010.

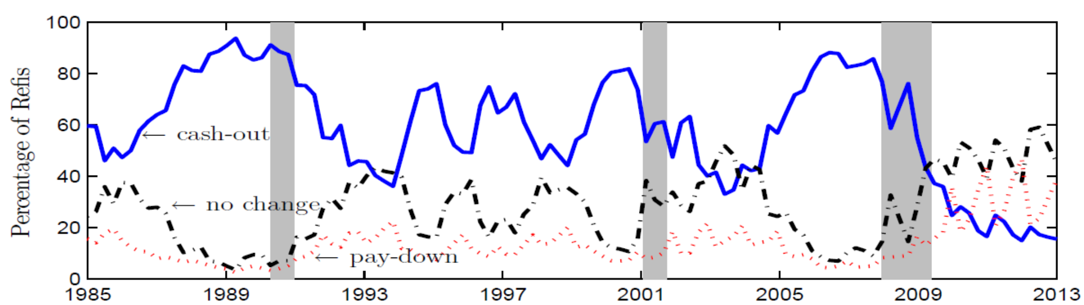



**Figure 13 Historical national breakdown of refinance types. Reproduced from Chen, Missoux, and Roussanov (2013). Grey bands indicate recession years.**

Our DC MSA loan data does provide the aggregate number of loan refinances, and this can be illuminating with respect to reasons households refinanced. Figure 14 plots the fraction of all loans refinanced each month in the DC MSA overlaid by the prime mortgage rate. Not surprisingly, there is an inverse correlation suggesting that as rates drop, households refinance to lower their payment. The drop in interest rates from 2001 to 2004 might explain why the percentage of cash out refinances shown in Figure 13 drops during this period and then shoots up afterwards. Likely, this change in percentages is due more to changes in rate refinance than cash out refinance. The large percentage share of cash out refinances from 2004 to 2006 is likely due both to rising house prices and steady interest rates.

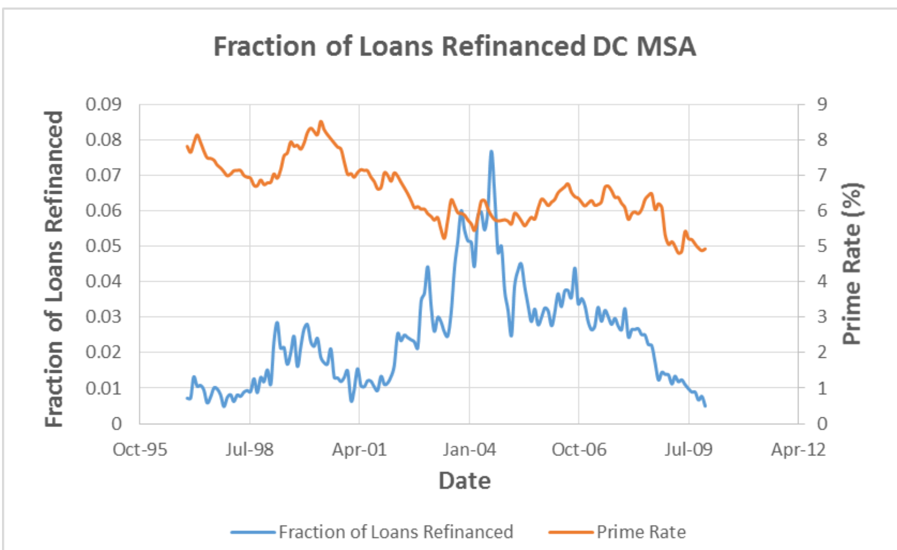



**Figure 14 Fractions of loans refinanced per month in the DC MSA versus the prime rate. Graph derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

Figure 15 digs a bit more deeply into the relationship between interest rates and refinance. This figure plots loan moneyness, which is the difference between the current prime rate and the prime rate when the loan was originated[3]. In other words, a moneyness of -3 implies a 3 percentage point drop in prime rate between loan origination and the current time. Not surprisingly, the lower the moneyness, the higher the likelihood of a refinance. Note that due to teaser rates on ARM loans, a borrower could receive a lower immediate interest rate when refinancing one loan whose teaser rate has expired into a new loan with a new teaser even though the moneyness (expressed as change in prime rate) is positive. This explains why ARM loan refinance probabilities are less correlated with moneyness as defined in this paragraph.

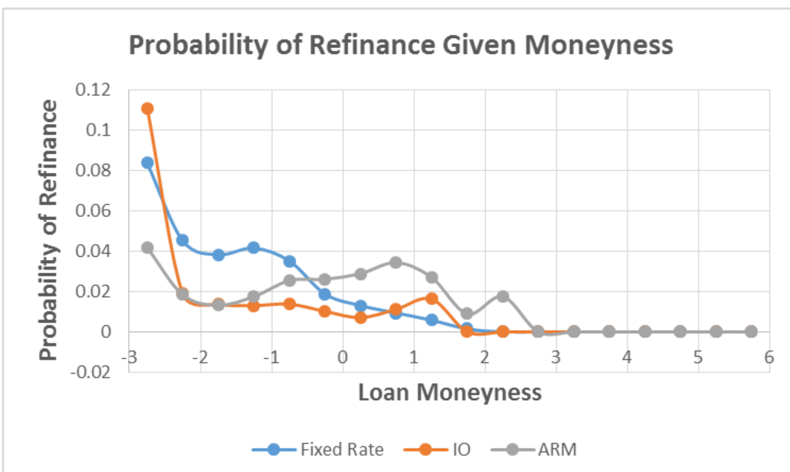



**Figure 15 Probability of refinancing with respect to the moneyness of the loan. Graph derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

[3] A better definition would compare the loan's interest rate with the rate the borrower could get on a new loan. However, measuring this quantity is difficult because a potential borrower's attainable interest rate is only observable if the borrower obtains a loan. Also, rates on ARM loans follow a complex schedule.

The final terminal loan state are home sales. I describe data used to calibrate and parameterize this aspect of the model in the next section on DC area Multiple Listing Service (MLS) data.

## 2.2. Real Estate Market Data

Real estate market data provides insight into the underlying dynamics of the housing market, and we use some aspects of this data to calibrate model rules and some as targets for model output. Our main source of real estate data comes from the Washington DC Multiple Listing Service (MLS). The MLS database records each time a seller lists a house for sale, updates its listing, delists, or sells its house. Using this information, we calibrate sellers' behaviors in terms of setting initial listing price and updating the price. Moreover, we compute a number of market statistics that we use as targets for model output, including average house price, distribution of prices, units sold, average days on market, and average ratio of sale price to original listing price. Note that the MLS data only contains information on houses listed in the MLS database, but this represents a large fraction of housing market activity.

Figure 16 presents the distribution of house prices for the month of January in 1997 (prior to the bubble), 2005 (near the peak), and 2008 (near the trough). The distribution of house prices is a key data item to which we compare model output, but we do not use this prices as an input. Not surprisingly, the distribution of prices is lower in 1997 than the two later years. However, interestingly the price distribution in January 2005 is almost exactly the same as that in January 2008.

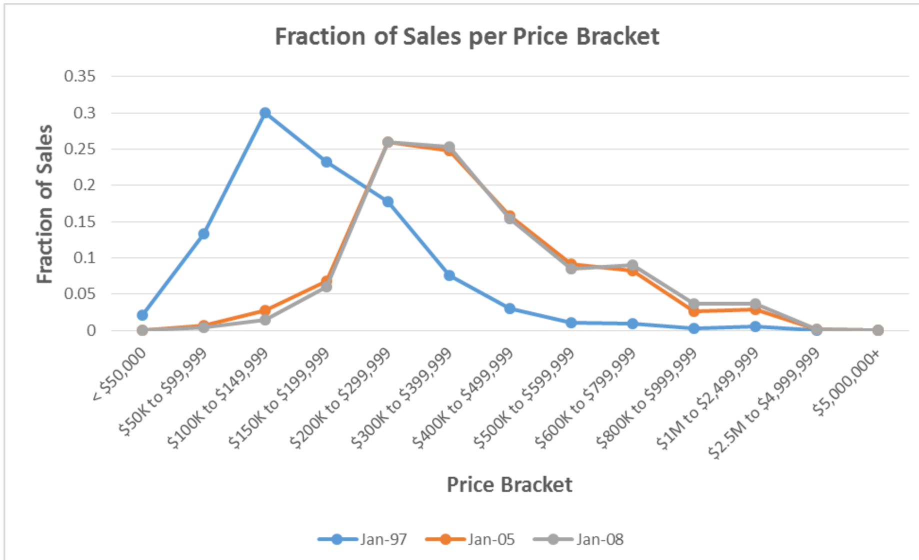



**Figure 16 Fraction of home sales per price bracket, comparing January in 1997, 2005, and 2008. Graph derived from data provided by the Washington DC Multiple Listing Service.**

Figure 17 displays the number of sales recorded per month in the MLS data (again, note that this is not the universe of all sales). This graph displays considerable seasonality representing the fact that many home sales occur in the summer, possibly because this is between school years. The graph also shows a notable trend with sales peaking in early 2006 near the height of the bubble and dropping off sharply afterwards. Although Figure 16 shows that the distribution of house sale prices in January 2005 and January 2008 is almost identical, Figure 17 reveals that the total sales in these months are quite different. In fact, there were 6,220 house sales recorded in the MLS database in January 2005 compared to only 2789 in January 2008.

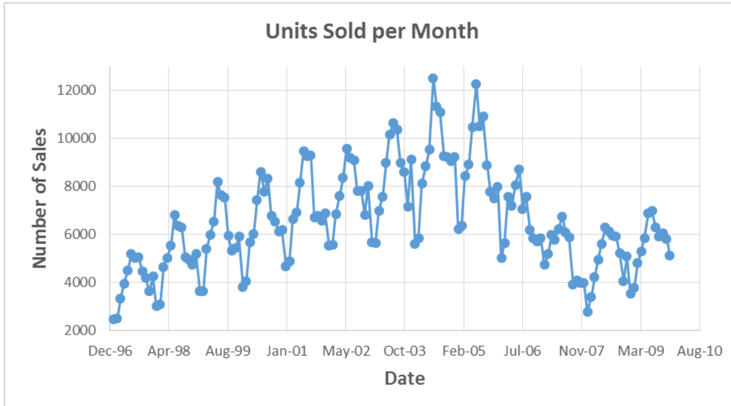



**Figure 17 Units sold per month. Graph derived from data provided by the Washington DC MLS.**

Beyond simple summary output statistics, we can compute more detailed market data. Days on market (DOM) refers to the number of days a house is listed before it is sold, and a "hot" market is typified by a low DOM. Figure 18 plots the average and median DOM for houses sold each month. Again the data shows significant seasonality, and not surprisingly DOM drops very low during the height of the bubble. In fact, the median falls below one week for several months during the bubble years.

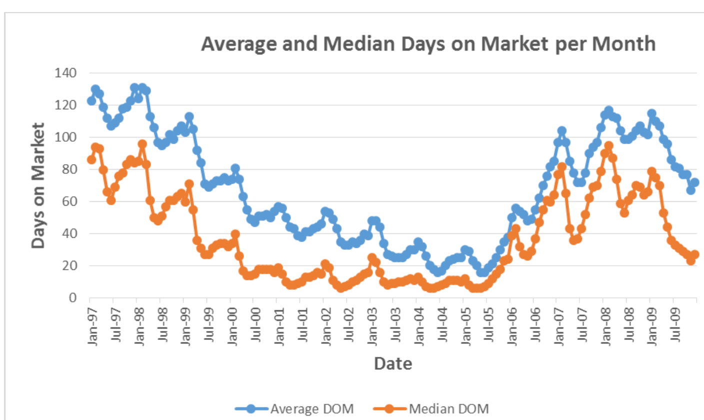



**Figure 18 Average and median days on market. Derived from data provided by the Washington DC MLS.**

Another measure of how "hot" the market is at any given time is the ratio of the price a seller actually receives compared to the seller's original list price (OLP). Figure 19 plots the average value of this ratio. As with other measures, average sale price to OLP peaks during the bubble year, reaching almost 1.0 in many months in the early 2000s. There were some months where average sale price to OLP was reported well above 1.0 (e.g., reported as above 58.9 in August 1997) so I cut off the chart at 1.0 to exclude these suspicious values.

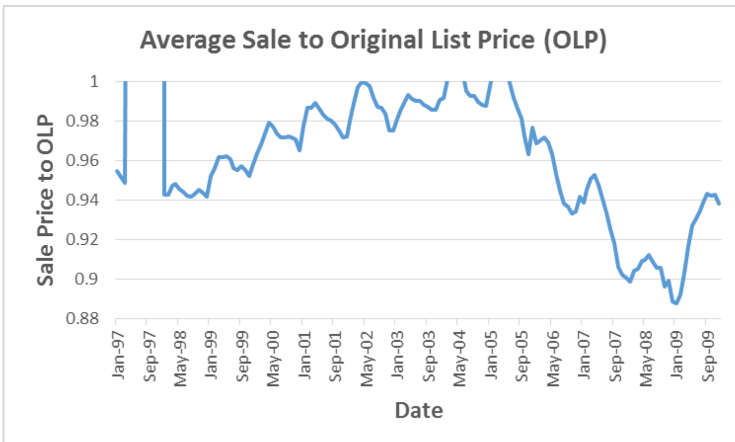



**Figure 19 Average sale price to original listing price. Graph derived from data provided by the Washington DC Multiple Listing Service.**

Beyond these plots, the MLS data was useful in calibrating seller behavior in setting initial list price, determining when to delist, and determining how and when to markdown unsold homes. Chapter 5 provides some discussion of this calibration.

Another source of housing market data is the Housing Vacancy Survey (HVS). This data provides information on the vacancy rate and homeownership rate. HVS defines a house as vacant if no one is living in a house at a particular time or even if the house is occupied, the occupants have a usual residence elsewhere. Thus, a single household can only occupy one house even if the households owns multiple houses. The homeownership rate measures the fraction of households in the Washington DC MSA who own a house. Figure 20 plots the vacancy and homeownership rates from the HVS. Homeownership rate rises steeply from 1998-2001, remains flat until 2007, and then drops from 2007-2009. Although this follows the housing market movements generally, the peak precedes the market peak, suggesting changes in homeownership rate might have some predictive power in identifying future price trends. The vacancy rate generally follows the course of the crisis, staying low—except for an anomalously high value for 2003—during the boom years and rising during the crash. The model uses the 1997 value of these variables for initial conditions and the rest of the time series as an output target.

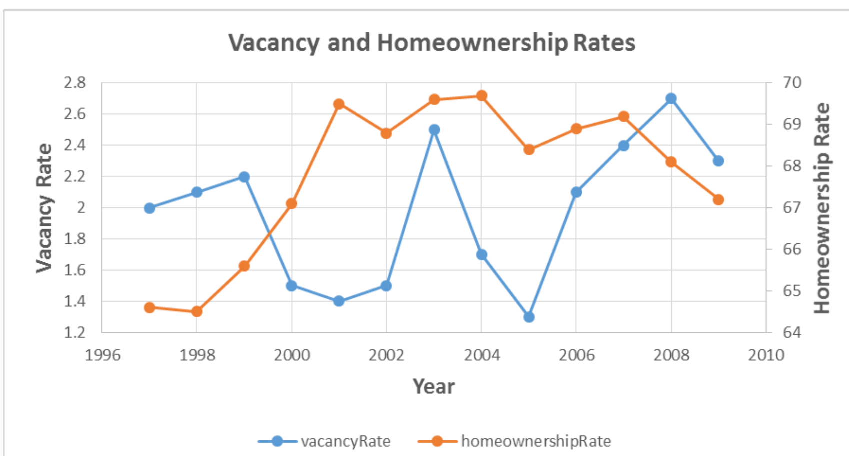



**Figure 20 Homeownership and vacancy rates. Graph derived from Housing Vacancy Survey data.**

## 2.3. Demographic Data

Demographic changes in a region, although not central to the general theories about the housing crisis, are important for understanding the particular course of the bubble and crash in a region. One key component of demographics is simply the number of households in the region, especially when juxtaposed against the number of houses. Figure 21 shows the number of households in the DC MSA derived from Internal Revenue Service (IRS) data and the housing stock inferred from IRS and Housing Vacancy Survey (HVS) data. Determining the empirical housing stock is actually quite challenging. The housing market model specifically models single family houses, not rental units or multi-family houses and obtaining clean estimates of this stock was difficult. Therefore, we inferred the housing stock using the household population (from IRS data) combined with the vacancy rate and home ownership rate from the Housing Vacancy Survey (HVS). For a particular year we set $S = {}^{P * O}/_{1 - V}$ where S is the housing stock, P is the household population, O is the home ownership rate from HVS, and V is the vacancy rate HVS. Note that Figure 21 shows housing stock increasing faster than population during the bubble years. Since housing stock quantifies supply and household population is a main factor in demand (the others being homeownership rate and the demand for investment properties), this graph suggests that one issue leading to the housing market crash might have been insufficient demand.

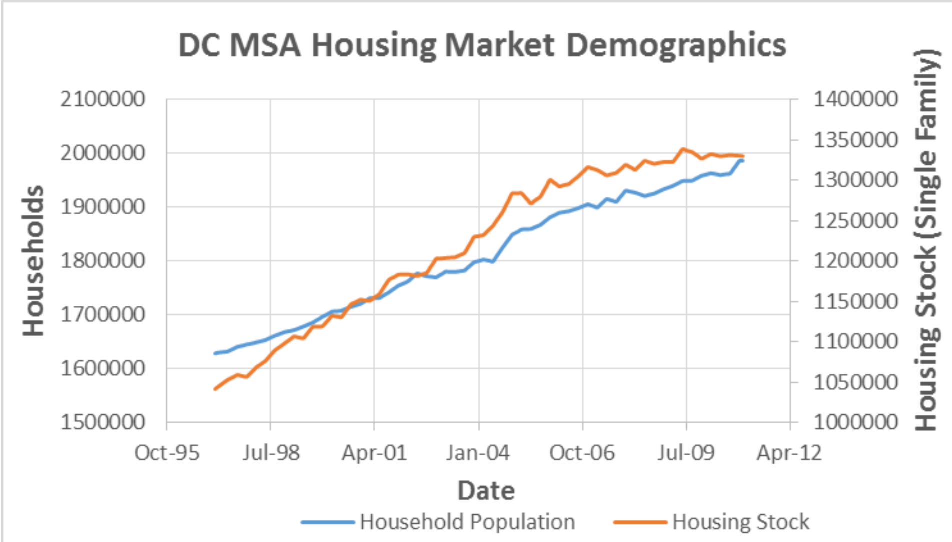



**Figure 21 Empirical estimate of number of households and houses in the DC Metro region from 1997 to early 2011. Household population data derived from Internal Revenue Service data. House population inferred from combination Internal Revenue Service and Housing Vacancy Survey data.**

Because ABMs naturally model heterogeneous populations, both houses and households have individual attributes. For houses, we boiled down all attributes of a house (e.g., location desirability, square footage, condition, etc.) into a single value, which we term house quality. We derived the quality distribution of houses using historical sale price distributions, scaling prices by the Case-Shiller house price index in the month the houses were purchased. Figure 22 displays the distribution of house quality for the DC MSA, omitting all qualities above one million. The actual model uses the full distribution, including the long upper tail of houses with quality above one million, but the figure omits the tail to better show the shape and skewness of the rest of the quality distribution. This distribution (including the tail observations above one million) fits a lognormal with $\mu = 12.06$ and $\sigma = 0.563$ fairly well (Kolmogorov-Smirnov D-statistic =

0.023). In the model we simply draw house quality from the empirical distribution with replacement rather than use the lognormal.

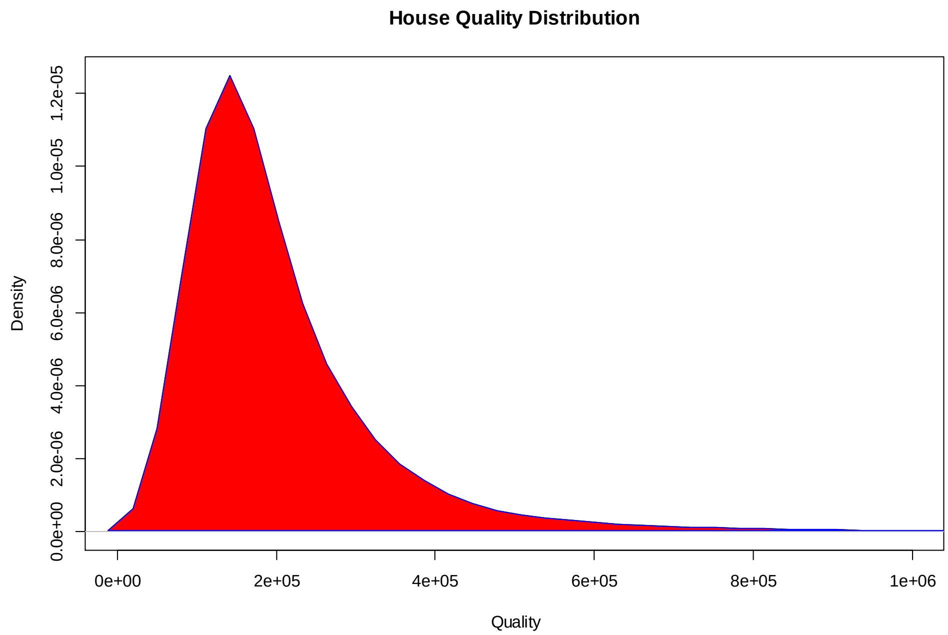
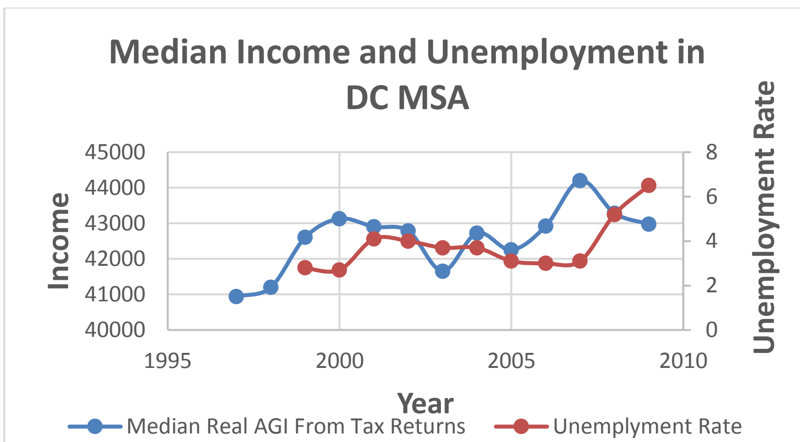


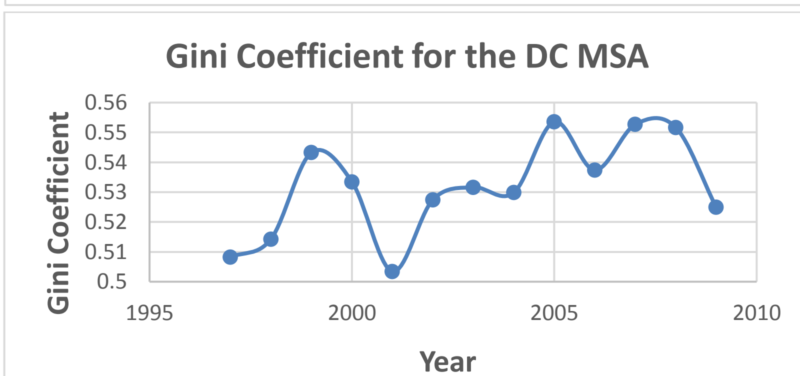

**Figure 22 Distribution of house quality, omitting houses with quality > 1M. Graph derived from data provided by the Washington DC Multiple Listing Service.**

Households in the model have three heterogeneous variables: income, wealth, and age. For household income, we received IRS data for the DC MSA from 1997 to 2009. Shifts in household income can produce market fluctuations; for example, a steep rise income might lead to increases in house prices. Figure 23(a) shows how income and employment changed in the DC MSA. The blue line plots the median adjusted gross income from tax returns filed with the IRS for the DC MSA, and the red line is the unemployment rate. Note that the income line displays household adjusted gross income

(AGI), which might combine multiple wage earners within a household, whereas the unemployment rate is computed on a per worker basis. In general, there are no large swings in either plot during the bubble, but unemployment did shoot up from 3.5% to 7% from 2007 to 2009. This suggests income might have been more of a factor in the housing crash than the housing bubble. Figure 23(b) displays the gini coefficient computed on tax return AGI. There is no discernable trend in this data. Note that the US number is around 0.4 during this period as computed by the World Bank.




(a)




(b)

**Figure 23 (a) Median adjusted gross income (AGI) and unemployment rate for the DC MSA (b) Gini coefficient computed on the AGI observations from IRS tax returns for the DC MSA. AGI data provided by the Internal Revenue Service. Unemployment rate data is from the Bureau of Labor and Statistics.**

Wealth is also an important determinant in housing activities. Unfortunately, we could not obtain wealth data for the DC area, and importantly we could not obtain joint distributions of wealth and income. Therefore, we use the national wealth distribution from the Panel Study on Income Dynamics (PSID), and although we do not enforce a specific correlation between income and wealth, the behavioral rules in our model (including consumption, saving, and income evolution) help ensure a reasonable relationship between these variables.

## 2.4. Model Use of Data

The housing market model is a combination of a large amount of empirical data as well as theoretically and empirically estimated behavioral rules. The model uses data in two main ways: to constrain agent behavior and attributes and to compare model output to empirical data. First, the model execution must be constrained by as much empirical data as possible. For example, since we know the empirical distribution of income for Washington Metropolitan Statistical Area (MSA), agents in the model should be constrained to follow that distribution and not allowed unrealistic incomes. Similarly, the model should not rely on unrealistic models of default, refinance, or selling behavior. All of these behaviors can be calibrated from data, and agent behavior should be constrained to follow this calibration. Second, output data, such as house prices, house price index, and house quantity as well as secondary outputs, such as time on market, number of refinances, and distribution of loan-to-value ratios should evolve endogenously in the model and be compared to empirical output data. The degree to which the endogenously generated outputs match empirical data determines how valid the model is for policy and counterfactual analysis.

More specifically, model logic follows several design principles with respect to use of empirical data.

1. Where possible, directly clamp agent attributes to empirical data. For example, the model enforces that agents in the simulation have the same income distribution as observed in empirical data by adjusting the model evolved income distribution to fit the empirical distribution (see Chapter 3).
2. Where empirical data is present, but it is not possible to "clamp," use the data to inform agent behavioral rules. For example, we can derive the probability of strategic default conditional on current loan-to-value ratio from empirical data and use this to determine an agent's probability of strategic default. It is not possible to clamp the number of strategic defaults since the distribution of loan-to-value ratios in the model evolves endogenously.
3. Where it is not possible to clamp or inform behavioral rules, use a theoretically justified behavioral rule and, if possible, calibrate the rule's parameters based on model output. Chapter 5 discusses a few instances where this was done, such as for the desired expenditure rule.
4. Never use empirical data for key output targets (e.g., average house price, house price index, quantity of house sold) and never use future data—i.e., empirical data for any period beyond the current date in the simulation.
5. Keep behavioral rules simple and theoretically or empirically justified.

# 3. BASE HOUSING MARKET MODEL

This chapter describes the base housing market simulation model. The goal of the model is to uncover the dynamics in the housing market that lead to bubbles and crashes. The base housing market model consists of a single type of agent: households and several non-agent objects, such as houses and loans. At each time step of the model, which represents one month, execution proceeds as follows

1. The model updates the agent population based on empirical demographic changes within the target region (which in this dissertation is the Washington DC metropolitan statistical area (MSA), but could be any MSA).
2. The model updates housing stock based on empirical data (i.e., adding and deleting homes from the housing supply).
3. Agents execute non-interactive behaviors, such as accruing wealth, listing their houses, refinancing, defaulting, etc.
4. Agents interact in the housing market in which they buy, sell, and rent houses.

## 3.1. Agent and Model Object Properties

Figure 24 provides a simple schematic of the state of the model at any given point in a simulation run. An agent-based model is a discrete time dynamical system so the state updates at defined time steps. As described previously, the main objects in the model are households (the agents[4]), houses, and loans. Each household has a total wealth made up its liquid wealth and home equity. The distribution of wealth in the population matches empirical data from the PSID as described later in this chapter. Similarly, each household receives an income. The income adjusts over time following a permanent income process similar to the one described by Carroll (Carroll 1997) —also described later in the chapter—and is adjusted to match the empirical income distribution for the DC metropolitan statistical area (MSA) from the Internal Revenue Service (IRS). Each household has an age approximating the age of the top wage earner in the household. Age influences when the household enters the housing market and when the household leaves the simulation (i.e., through death or migration) to be replaced by a new younger household.

[4] Note that we do not always run the model with one agent for every household in the DC MSA. We can scale the data so that, for example, we run with 1/10$^{th}$ the number of agents as households. Everything remains distributionally the same (e.g., the same income and wealth distribution), but absolute numbers, such as the number of households, houses, listings, etc. scale. Later in this chapter, I investigate how to determine the scaling factor.

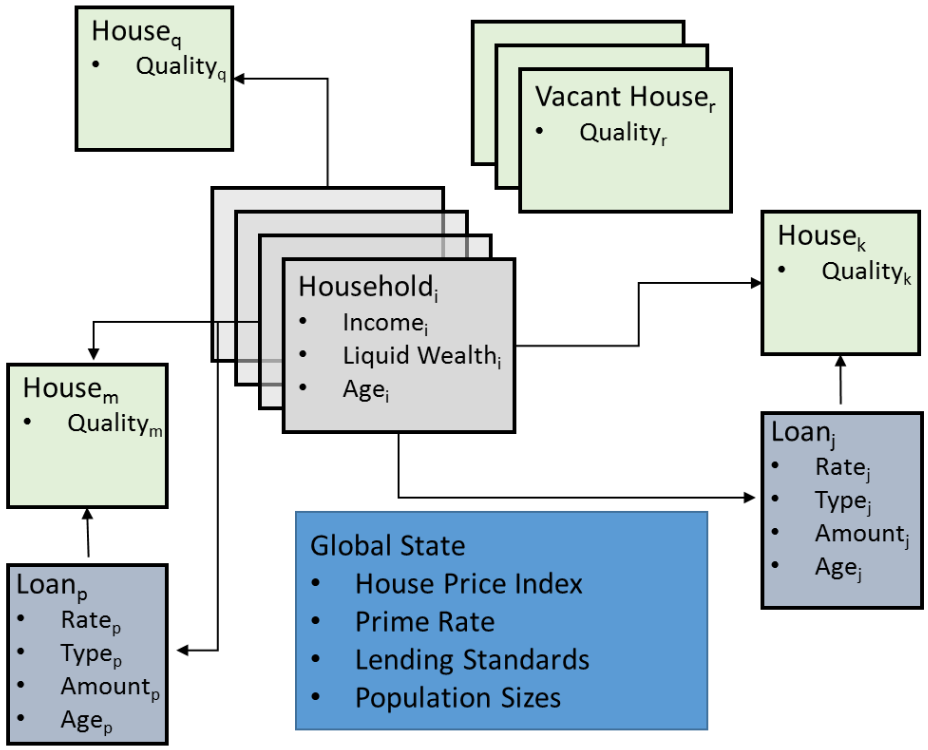



**Figure 24 Simple schematic of the house price model state.**

Income, wealth, and age are demographic properties of households that affect their behavior. In keeping with model philosophy, these properties evolve endogenously based on theoretically and empirically justified rules (e.g., the Carroll process for income), but then the model forces them to match empirical data. Although, we do not have information on how income and wealth are correlated for the DC MSA, the endogenous income and wealth process ensures the correlation matches typical economic models. Beyond these demographics, other agent properties include the houses and loans the households own and the household's credit history.

Each house in the model is described by its "quality" which models the intrinsic or "fundamental" value of the house. For each house in the model, all agents perceive the same quality, and a house's quality does not change except during a foreclosure event (in which case the house quality drops in half). All else equal, if one house has a quality twice that of another house, all agents would pay twice as much for the first as the second house. A future extension can test whether heterogeneity in agents' house valuations affects model dynamics. The previous chapter describes how we determined the empirical distribution of house qualities in the DC MSA.

Loans in the model can be one of three types: fixed rate, adjustable rate (ARM), and interest-only. All loans are 30 year loans. Interest only loans convert to ARM loans after the initial teaser period expires. As described in the next section, the model ensures that the simulation matches empirical distribution of loan types (conditional on debt-to-income ratio) and interest rates (conditional on loan type and debt-to-income ratio) in aggregate. Because the data on loans is from LoanPerformance[5] which includes only non-agency loans (i.e., those not guaranteed by a government sponsored entity, such as Fannie Mae or Freddy Mac), some of this data might be skewed. Note we did weight each loan in our empirical sample from LoanPerformance so that the annual bivariate distribution of loans at origination by FICO and LTV matched known distributions.

[5] Further work on the Housing Market project did incorporate loan data from CoreLogic which contains a more comprehensive set of loans. The version of the model used in Chapter 4 replaces the LoanPerformance data with CoreLogic data. Note that in neither CoreLogic nor the LoanPerformance data sets were loans matched to actual addresses nor did we attempt to do so.

## 3.2. Model Logic

This section describes agents' behavior and model execution logic. Although there is a lot of detail in this section, the actual execution of the model at a high level is simply the four steps described earlier:

1) Update agent population based on empirical data
2) Update house stock based on empirical data
3) Agents do non-interactive behaviors simultaneously (refinance, default, listing house, getting pre-approved for a loan, accruing income, etc.)
4) The housing market executes matching buyers to sellers

The model time step is one month, and the base model simulates the period 1997 to 2009 for the Washington DC MSA (which includes both DC suburbs around the city).

Figure 25 provides pseudo code of the entire model. The rest of this chapter explains the model in detail. Readers can refer back to this pseudo-code as I explain the model logic. In Figure 25, I call out specific slots for behavioral rules, such as the rule households use to decide to list their house (called out in bold as the "House List Rule") or the rule households use to set their desired house expenditure (called out in bold as the "Desired Expenditure Rule"). I coded the model to allow these rules to be easily updated and so that different agents could have different implementations of the rule. The rest of this chapter fills in the actual model logic fulfilling these rule slots. Intentionally, Figure 25 only provides the model execution framework so I do not go into detail on the rule implementations in this pseudo-code.

**Run Model**
  Run Setup Module
  For $t$ = 1:1200 // 100 yr init removes transients and gets representative correlations of agent attrs.
    Init timestep($t$)
    Run timestep ($t$)
  For $t$ = 1201:1355 //represents one month timesteps from 1997 to 2009
    Read forward empirical data 1 month
    Init timestep($t$)
    Run timestep ($t$)
    Output statistics
**Setup Module**
  Read in source data files
  Run Create House Module $m_0$ times where $m_0$ = # of houses in Jan 1997
  Run Create Household Module $n_0$ times where $n_0$ = # of households in Jan 1997
**Create House Module:**
  Create new house object
  Assign house a random quality from empirical distribution
  List house for sale, setting initial list price = House Price Index * Quality
**Create Household Module:**
  Create new household agent
  Assign a random age drawn from empirical age distribution //representing age of head of household
  Assign a random permanent income drawing from empirical income distribution.
  Set transitory income = permanent income
  Assign a random liquid wealth drawing from empirical liquid wealth distribution
**Init Timestep Module (time = *t*): //** Updates both agent population and house stock
  Set $aged\text{-}out_t = 0$
  For $i = 1{:}n_{t-1}$ households
    Age household$_i$ one month
    If household$_i$ ages out (probability dependent on age)
      Increment $aged\text{-}out_t$
      Remove household$_i$ from simulation and list owned houses for sale
    Else
      Once every 12 months assign new transitory income to household$_i$
  Update Household Population by running Create Household Module $[n_t - (n_{t-1} - aged\text{-}out_t)]$ times
  Once every 12 timesteps, run Carroll process to set permanent incomes and clamp to empirical
  Once every 6 timesteps, clamp liquid wealths to empirical distribution
  Update House Population by running Create House Module $[m_t - m_{t-1}]$ times
**Run Timestep Module (time = *t*): //** Agents execute non-interactive behaviors; then the market runs
  For $i = 1{:}n_t$ households
    $Liquid\text{-}wealth_t = Liquid\text{-}wealth_{t-1} + Income_t - (0.025 * Liquid\text{-}wealth_{t-1} + 0.6 * Income_t)$
    Determine Housing Behaviors depending on household state:
      RENTER: run Renter Module
      HOMEOWNER NOT DEFAULTED: run Homeowner Not Defaulted Module
      HOMEOWNER DEFAULTED: run Homeowner Defaulted Module
      MOVER: run Moving Module // Used for households who sold home last time step
  Run Housing Market Module
**Renter Module**
  Pay Housing Costs: $Liquid\text{-}wealth_t = \text{Max}(0, Liquid\text{-}wealth_t - rent_i)$
  If rental contract is complete
    Run **Become-Buyer Rule**. If rule returns *true*
      Get LoanApproval by running Buyer Demand Module
      Add to Buyers List for Housing Market Matching Algorithm
    Else

Sign new rental contract for term in U(0, 12) and $rent_i$ = 0.2 * $income_i$
**Homeowner Not Defaulted Module**
Run **strategic default rule**. If rule returns *false*
Pay mortgage costs: $Liquid\text{-}wealth_t$ = Max (0, $Liquid\text{-}wealth_t$ – *monthly-payment* – *past-due-amt*)
Pay insurance, maintenance: $Liquid\text{-}wealth_t$ = Max (0, $Liquid\text{-}wealth_t$ – *house-value* * 0.045)
If House is Listed
Run **House Delist Rule**. If rule returns *true*,
Delist house
Else
Update house price (either markdown by fraction and leave unchanged)
Else
Run **House List Rule**. If rule returns *true*,
List house, setting initial list price = House Price Index * Quality * Markup
Else
Run **Rate-refinance rule.** If rule returns *true*
Get new loan at current LTV using **Loan Type Rule** and **Interest Rate Rule**
Else
Run **Cashout-refinance rule.** If rule returns *true*
Get new loan at LTV = orig LTV using **Loan Type Rule** and **Interest Rate Rule**
Else
Transition household to defaulted
**Homeowner Defaulted Module**
Do nothing and wait to be kicked out of house
**Moving Module**
Get LoanApproval by running Buyer Demand Module
Add to Buyers List for Housing Market Matching Algorithm
**Buyer Demand Module**
Set *desired-expenditure* by running **Desired Expenditure Rule**
Set *desired-LTV* by running **Desired Leverage Rule**
Set *loan-type* by running **Loan Type Rule**
Set *loan-rate* by running **Interest Rate Rule**
Adjust parameters to fit constraints (household wealth, leverage ceiling, and debt-to-income ceiling) using **Buyer Demand Rule**
**Housing Market Module**
Shuffle Buyers
for *b*=1:numBuyers
If there is a listed house whose list price ≤ maximum approved expenditure in Loan Approval
Purchase highest quality house list price ≤ maximum approved expenditure
Buyer receives loan specified in Loan Approval (adjusting purchase price = list price)
Transition Seller to Moving
Delist House
Else
Sign new rental contract for term in U(0, 12) and $rent_i$ = 0.2 * $income_i$

**Figure 25 Pseudo Code Description of Housing Market ABM**

### 3.2.1. Step 1: Update Agent Population Based on Empirical Data

The model time step begins by adjusting the population of households in the simulation to match the empirical data shown in Figure 21. The model simply reads the empirical delta population for the current month, and creates enough agents to make up for this delta. Each existing household agent in the simulation ages one month. With probability dependent on age, the household might "age out"—i.e., leave the simulation. The model replaces each household aged out in this manner by a randomly generated household. Any houses owned by the aged out household are listed for sale. Note that there are some months when the empirical number of households decreases (e.g., June 2012 to July 2012). To keep the modeled population consistent with the empirical data, the model does not replace some of the aged out households in these months.

Next, the model updates the income and wealth of the agents in the model to match empirical data. For income, the model matches distributional data acquired from the IRS for the DC metro area. For wealth, the model matches distributional data acquired from the Panel Study of Income Dynamics (PSID). However, the PSID data is not broken down by region so we used the national data.

Household income follows a Carroll process (Carroll 1997) to rank households, and then the model "clamps" the households to empirical data, preserving the ranking obtained in the Carroll process. The Carroll process assigns each household a permanent income *($P(t)$)* based on the previous month's permanent income, a growth parameter ($\gamma = 1.02$ in our simulation), and a shock parameter ($\kappa$, which is distributed lognormally):

$$P(t) = \gamma * P(t-1) * \kappa \quad (2)$$

The Carroll process then assigns each household a transitory income based on its permanent income and a lognormal shock:

$$T(t) = P(t) * \eta \quad (3)$$

Moreover, each household has a probability of transitioning to "zero income" for some number of months[6]. The transitory income of these households is set to 0.

Using the transitory incomes set by the Carroll process, the model next "clamps" the incomes to the empirical data. The model ranks every household by transitory income from Equation (3) and then draws *n* incomes from the empirical income distribution where *n* is the number of households. The household with the highest income based on the Carroll process receives the highest income drawn from the empirical distribution; the next highest ranked household by the Carroll process gets the second highest drawn income; and so on. In this manner, the model both captures households' income evolution as they age and ensures the aggregate distribution of income maps to the empirical data. Income still increases in general for a household as it ages (i.e., it moves up the income

[6] "Zero income" events model sudden drops in income, such as through job loss. Of course, with unemployment insurance, job loss does not mean zero income immediately. However, as described in the next few paragraphs, the Carroll process merely establishes the income rank of each household and the actual amount of income comes from empirical data. Thus, the term "zero income" should not be taken literally.

ranks) so that mortgage payments get easier over time—except of course if a household becomes unemployed, cash out refinances, buys a bigger house, etc.

The model clamps the liquid wealth distribution to empirical data as well. Household liquid wealth evolves based on income, expenditures, and housing market activity (see description later in this section), but as with income, the model ensures the aggregate wealth distribution matches empirical data. The wealth clamping process occurs every six months (although this is configurable), and proceeds similarly to the income clamping process.

### 3.2.2. Step 2: Update House Stock Based on Empirical Data

After updating the household population to match empirical data, the model next does the same for the housing stock, again following the demographic data as shown in Figure 21. For months in which the house stock increases, the model generates a new house, assigns it a quality by drawing from the house quality distribution, and lists the house for sale (later in this chapter, I describe how the housing market operates). For months in which the house stock decreases, the model removes random vacant unlisted houses from the simulation. If not enough of those houses exist, the model "sells" random listed houses at the current market price to no one and then removes the house from the simulation.

### 3.2.3. Step 3: Agents Execute Non-Interactive Behaviors Simultaneously

Agents execute the following non-interactive behaviors:

Update liquid wealth (note household wealth is composed only of liquid wealth and home equity): households receive income based on their assigned income from the Carroll process and expend 60% of their income and 2.5% of their liquid wealth on non-housing consumption:

$$W(t) = 0.975 * W(t-1) + 0.4 * I(t) \tag{4}$$

$W(t)$ is liquid wealth at time $t$ and $I(t)$ is income at time $t$. Note these expenditures do not include housing costs which are handled separately. If we assume a household attempts to spend about 1/3 of its income on housing, along with other expenditures, this equates to households holding about two to three months of income in liquid wealth—a number that matches well with Pew's Family Balance Sheet study. As described previously, wealth evolves through income, expenditures, and housing activity, but every six months is clamped to empirical data in a rank preserving manner.

Pay housing costs or default: Going into a time step, a household might be in one of six situations: a renter, a homeowner with no loan, a homeowner with a loan that is current (i.e., the homeowner has not underpaid in the past), a homeowner with a loan that is behind but is trying to catch up, a homeowner who has strategically decided not to pay its loan, or a homeowner in foreclosure[7]. For each of these six situations, the model logic is slightly different.

[7] Households can only own one house in the version of the model described in this chapter. Later versions of the model added the ability for households to own multiple houses.

1. *Renter*: renters simply pay their rental cost each month. If a renter does not have enough liquid wealth, the renter pays all its wealth (presumably the renter has moved to a cheaper unit).
2. *Homeowner with no loan*: homeowners spend on average 2.5% of the value of their house in maintenance cost per year (some homeowners more, some less). Homeowners also pay taxes and homeownership fees of about 2% per year. If the homeowner does not have enough money for maintenance, the homeowner simply skips the maintenance.
3. *Homeowner with current loan*: In addition to the maintenance expenses, a homeowner with a current loan also pays its monthly payment and possibly mortgage insurance. Note that before payment, the home owner does a calculation to determine whether it should strategically default (see below). Also, a homeowner might not have enough money to make its monthly payment in which case it becomes delinquent, although it will make a partial payment up to the entirety of its wealth.
4. *Homeowner with delinquent loan*: The logic of a homeowner with a delinquent loan is the same as for that with a current loan, except that this homeowner attempts to pay both its current monthly payment and any missed payments (plus applicable interest).

5./6. *Homeowner who has strategically defaulted* and *homeowner who is in foreclosure*: In both of these cases, the homeowner pays nothing and waits to be kicked out of its house.

Households strategically default based on the loan to value (LTV) of their house. A household "strategically" defaults when it decides it is not worth it to own a particular house. This might be because the household owes more money on the house's loan than the house is worth. Archer and Smith (2010) analyze defaults and give the two leading causes as a high (greater than one) loan to value ratio and a high ratio of monthly mortgage payment to income. The latter cause—that of high debt commitments compared to income—manifests itself through a household's inability to pay its mortgage (e.g., case four in the list above), which can lead to default and foreclosure. However, as long as the household has positive equity, it should not strategically default due to high monthly debt burdens. Households only strategically default due to high loan to value. Recall that in Figure 12 using data from LoanPerformance, we estimated the probability that a household strategically defaults conditional on LTV. At each time step, a household who owns a loan and has not previously strategically defaulted, decides whether to strategically default using the probability of default conditional on LTV from Figure 12.

Note that once a household becomes delinquent—either strategically or because they lack wealth to pay their mortgage—the household must fall 12 months behind on payments before foreclosure proceedings begin. It then takes 24 months before the household is kicked out of their house. Once this happens, the house is owned by the "banking system" and the house's quality is cut in half due to the depreciation that foreclosure usually causes. A homeowner who defaults cannot get a loan for some number of years (seven in the simulations in this dissertation) due to bad credit and must rent during this time period. Thus, many correlated defaults leads to a decrease in the overall pool of buyers and decreased housing demand.

Determine housing activities: Next the household determines whether it wants to refinance (if it has a loan), list its house (if it owns one), or try to buy a house (if it does not own a house).

A household might refinance either to lower its monthly payment or to increase its liquid wealth by converting home equity into liquid wealth. Households rate refinance with probability based on the type of the loan and the loan's moneyness. Moneyness measures the difference between the current prime rate and the prime rate when the loan was originated. Figure 15 gives the empirical probability of refinance based on loan type and moneyness estimated from LoanPerformance data, and the model uses these numbers. The model also ensures that monthly payments decrease as a result of rate refinance enough to recoup the refinance cost (= $5,000 in runs in this dissertation) in five years.

For cash out refinance, the model follows the linear rule estimated in Khandani et al. (2009). Specifically, households' probability of cash out refinance scales linearly as its home equity increases (i.e., its LTV decreases):

$$P(Refinance) = k * \frac{l - LTV}{l} \tag{5}$$

Following the estimates in Khandani et al. (2009), the runs in this dissertation use $k$ = 0.009 and $l$ = 0.85, and both *LTV* and $l$ are specified on a 0 to 1 scale (rather than the 0 to 100 used in discussions in this dissertation). When LTV is greater than 85, households do not cash out refinance. If the household decides to cash out refinance—based on a random draw controlled by Equation (5)—it applies for a loan at the same LTV that its previous loan was originated. If the new loan returns a cash out value greater than the refinance cost (plus a bonus which equals 2 * refinance cost in the model), the household cash out refinances.

Households consider rate refinancing (i.e., to lower its monthly payment) before considering a cash out refinancing. Many analyses have shown that cash out refinancing increases household leverage, making housing markets susceptible to a market crash. For example, Hurst and Stafford (2004) showed that from 1991-1994, households cash-out refinanced $28B worth of home equity. Cash-out refinancing also plays a big part in Khandani et. al's (2009) ratchet effect hypothesis. On the other hand, Gorton (2008) puts more emphasis on rate refinancing—specifically the increased incentive to rate refinance once the teaser period of an ARM loan expires. Chapter 4 investigates both the removal of ARM loans and cash out refinancing and neither significantly altered the course of the housing bubble and crash.

Households decide to list their house for sale randomly with probability so that the number of listings matches empirical data from MLS on listings. For example, in the spring months more houses are listed than in the winter months (Figure 26). This allows the model to pick up some seasonality in the housing market. All listed houses follow the same basic algorithm for setting an ask price. The fundamental value of the house is the house price index * house's quality. The initial ask price is this fundamental value multiplied by a markup (chosen uniformly between 0% and 7% in the simulations in this dissertation). Every one to three months, the price then drops by a mark down factor (chosen uniformly between 0% and 3.5% in the simulations in this dissertation). The update frequency and markdown factor vary from house to house, but are consistent for a particular listing of a house. After the house has been listed for three months, there is a 5% probability that the house will be delisted. These various model parameters—markup, markdown frequency, markdown extent, and delist probability—were all empirically derived from MLS data.

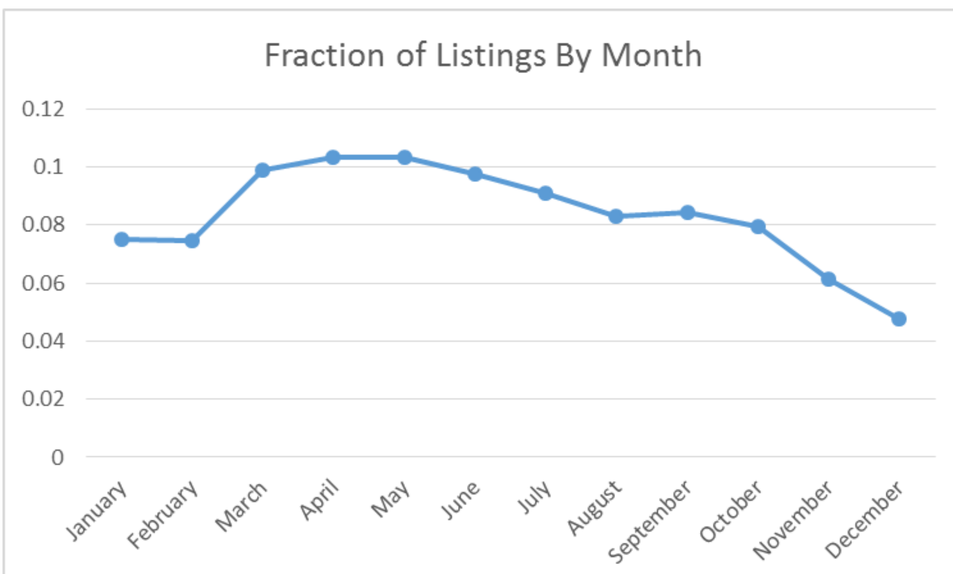



**Figure 26 Empirical fraction of house listings by month. Listings peak in the spring and trough in the winter. Graph derived from data provided by the Washington DC Multiple Listing Service.**

If a household does not own a house, this might be because the household is a renter or because the household just sold its house[8]. Renters have a lease period (randomly chosen from a uniform distribution ranging from 1 to 12 months), and when the lease period is up, renters decide whether to enter the housing market or continue renting. The decision to enter the housing market is a probability based on age. We did not have empirical data to determine these probabilities, but instead computed a distribution that matched the stylistic fact that most households enter the housing market between 25 and 40. Households that remain renters sign a new lease that costs 20% of their income at the time of signing.

A household that just sold its house or a renter that wishes to enter the housing market, first needs to be pre-approved for a loan. The household begins by determining the desired price of its new house by the formula:

$$D = \frac{\varepsilon * I}{3 * (\tau + c + r - a\delta(p) + bd)} \tag{6}$$

Where

- $D$ is desired house price
- ε is a parameter that models heterogeneity between agents (in runs in this dissertation ε ~ U(0.9, 1.1))
- $I$ is yearly income

[8] Note that households always sell before buying in the housing market model.

- $\tau$ is taxes, mortgage insurance, and home owners association fees (i.e., fixed non-mortgage expenses)
- *c* is maintenance expenditure (i.e., discretionary non-mortgage expenses)
- *r* is the prime rate for mortgages
- *a* is the "appreciation effect" and governs how much a homeowner believes house prices will appreciate or depreciate given recent history. Bubble and crash sizes (and model stability) are sensitive to this parameter, and we investigate this later in the dissertation
- $\delta(p)$ is the change in the house price index over the last 12 months
- *b* is the "LTV effect" and governs how much homeowners believe banks will require for downpayments.
- *d* average downpayment for new loans only counting the top 50% leveraged loans issued in the last 12 months.

This equation follows the rule of thumb that households spend about 1/3 of income on housing each month. This becomes clear when we rearrange the equation:

$$D * (\tau + c + r - a\delta(p) + bd) = \frac{\varepsilon * I}{3} \tag{7}$$

The left-hand side of this equation approximates monthly cost of mortgage including the household's expectation of increased or decreased equity (this is the $a\delta(p)$ term). The right-hand side is 1/3 of income multiplied by a heterogeneity factor. Note that the Bureau of Labor and Statistics (BLS) shows housing expenditures to be about 31% of expenditures and 28% of income for homeowners per year. The desired expenditure calculation attempts to hit a somewhat higher 33% number because over the life of a loan, a household's income typically increases through permanent income growth and also the loan negotiation process and housing market (see below) often lowers the actual purchase price for which a homeowner is approved. Note that the BLS number is for the general population not new loan issues, and we would expect that DTI goes down on average over the life of a loan.

Next, the household determines its desired downpayment. Using LoanPerformance data, the model draws a loan to value (LTV) at origination based on the distribution of LTVs at origination in the historical data for a particular year, dependent on total house price. The LTV data is actually combined LTV (CLTV) which measures the total value of all loans a household uses to buy a house. For simplicity, a household in the simulation gets a single loan that encompasses the combined value of all loans.

The household now has a desired expenditure (DE) and a desired leverage (LTV). For various reasons, this pair might not be feasible. For example, imagine a household wants to buy a \$500K house with an LTV of 0.8, meaning the household needs to put down \$100K. The household might not have \$100K of wealth. Alternatively, the monthly payment for a \$400K loan might be too much for the household's income. The model adjusts LTV and DE so that the household can meet both its downpayment and monthly payment obligations (Figure 27). The wealth constraint is the line defined by $DE\ *\ (1 -$

$LTV) + CC = W$ where $CC$ are closing costs (set to 0 for this dissertation) and $W$ is liquid wealth. The debt-service constraint relates monthly payments to income. A buyer can only have up to *maxDTI* fraction of income devoted to housing expenses. In practice, because desired expenditure is chosen specifically so that households spend about 1/3 of their income on housing and *maxDTI* is around 0.6, this constraint is not usually binding.

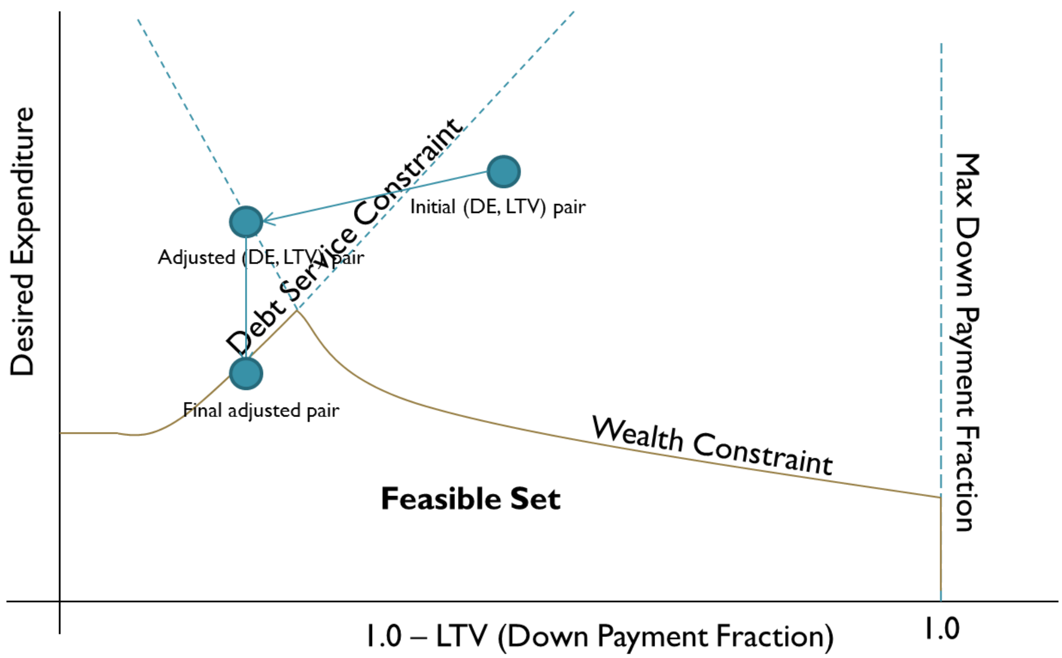



**Figure 27 Loan pre-approval adjustment process.**

The last piece in the preapproval process is the actual loan type and interest rate. The model chooses both of these based on historical frequencies. For loan type, the historical frequencies depend on LTV (i.e., the fraction of fixed rate, ARM, or interest only loans in a given year and given LTV), and the rate depends on both loan type and debt to income (DTI). Of course, there might be a slight adjustment in downpayment if the actual loan acquired has a different monthly payment than the one used in the preapproval adjustment process in Figure 27.

### 3.2.4. Step 4: Execute the Housing Market

The housing market pairs sellers with buyers. There are several ways in which a house might get listed for sale:

1. The house's owner decides to list the house (see the previous step in which this rule is governed by a random probability draw).
2. The house's owner ages out of the simulation (see step 1 on updating agent demographics).
3. The house is created as part of an increase in the housing stock (see step 2 on updating the housing stock).
4. The house was foreclosed upon (see step 3 on how the foreclosure process).

In all these cases, the listing follows the same algorithm outlined in the previous section. The house is initially marked up above the fair market value (where fair market value = house quality * house price index) and then progressively discounted if no buyer purchases it. There is 5% chance of delisting each month after the third month of listing. In the case of household owned houses, delisting means the homeowner pulls the house back from the market and continues to live in the house until deciding to move again sometime in the future. In the other cases, in which there is no household owner (e.g., the bank owns the house after a default), the house gets relisted the next month starting the process over. This one month pullback allows the list price to reset to match changes in market conditions.

Buyers enter the market with a loan pre-approved for a certain house size (see previous step on pre-approval process). The model randomly orders the buyers, and each buyer purchases the highest quality house whose ask price is below the buyer's pre-approved loan amount. The buyer then receives an actual loan preserving the interest rate and LTV agreed upon during the pre-approval process. Liquid wealth equal to the downpayment flows from the buyer to the seller, and the buyer takes possession of the house.

## 3.3. Architecture Design

Finally, although I do not focus the dissertation on the software architecture of the housing market ABM, it is appropriate to include a few remarks on the importance of the architecture and how a properly designed model can address the opacity problems of ABMs. ABMs often consist of a large amount of computer code, and reviewers do not always understand why a model produces a particular outcome. This opacity limits the ability of ABM researchers to discover and convey model results. One contribution of housing market ABM is the way in which I separated the behavioral rules from the model execution flow. This structure isolates the key theoretical elements of the model, increasing transparency and also permits sensitivity testing of the rules themselves. Such tests can identify which rules and assumptions drive key results.

For example, the household agent class encodes only the general process through which agents complete a time step—i.e., receiving income, consuming, deciding whether to refinance or default, etc. However, the actual behavioral rules reside in a separate class called HouseholdDecisionSupport. This class contains a set of rules that map to the different household decisions. Notice in Figure 28 that each rule—e.g., DefaultRule, RefinanceRule, etc.—is an instance of a particular class designed to encapsulate that rule's logic. Due to this design, it is natural to create multiple versions of each of these rules and assign a specific version to each household. The final piece of architecture is a configuration class that governs which rules are active in a particular simulation and how to allocate the rules to agents. This makes it easy to test different rules and rule mixes in the simulation and conduct the structural sensitivity analyses as described in this subsection.

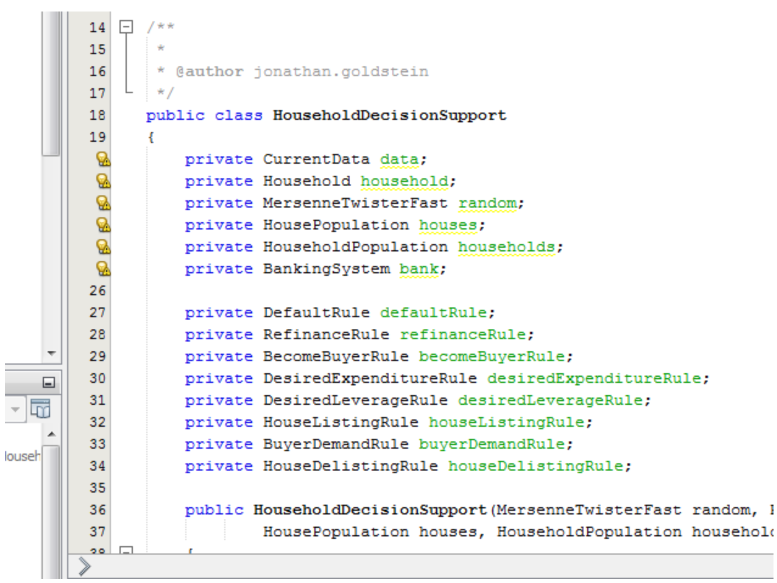


**Figure 28 Screenshot of HouseholdDecisionSupport class.**

# 4. MODEL OUTPUT AND COUNTERFACTUAL POLICY ANALYSIS

This chapter uses the housing market model to explore potential counterfactuals for avoiding the housing bubble. The chapter begins by showing the typical output of the model, which I call the base case. After some discussion of run to run variation, I present a set of policy explorations centered on leverage, interest rates, refinance, lending standards, and expectations. The explorations show that a mix of factors caused the housing crisis with leverage and expectations having the most effect on the course of the simulation.

## 4.1. Typical Output

This section describes the output of the model given typical parameter settings. First, I list the agent rules (Table 2) and parameter settings (Table 3) used in this run. The rules listed in Table 2 were all described in the previous chapter. The table simply serves to indicate the base set of rules that could be varied in future analyses (some of which are varied in Chapter 4). Similarly, many of the parameter values in Table 3 were described in the previous chapter. Many, such as permanent income growth or seller algorithm parameters, were estimated from empirical data, but others, such as the appreciation effect were not and will be varied in this and chapter and Chapter 5.

**Table 2 Agent behavioral rules used in base model runs**

| Rule Type | Use | Rule |
|---|---|---|
| **BecomeBuyer** | Determines when a household attempts to buy its first house | Probability based on household age |
| **DesiredExpenditure** | How a household decides how much to spend on a house | Equation based on expending 1/3 of income per month rule of thumb |
| **DesiredLeverage** | How a household determines downpayment size as percent of house price | Empirical draw dependent on desired house price |
| **LoanType** | How the bank and borrower determine the type of loan (fixed, ARM, interest-only) | Empirical based on desired LTV |
| **Interest Rate** | How the bank and borrower determine interest rate of loan | Empirical based on estimated debt-to-income and loan type |
| **BuyerDemand** | Loan preapproval negotiation process | Given desired expenditure, desired LTV, loan type, loan rate, buyer wealth and income, LTV adjusts to satisfy wealth constraint, then expenditure adjusts to satisfy debt service constraint |
| **RateRefinance** | Determines when a household rate refinances | Empirical probability based on moneyness of loan |
| **CashOutRefi** | Determines when household cash out refinances | Follows linear rule in Khandani et al. |
| **StrategicDefault** | Determines when a household defaults even if it could pay its mortgage | Empirical probability based on current loan LTV |
| **HouseListing** | Determines when household lists its house for sale | Empirical probability whose value varies with historical listings |
| **HouseDelisting** | Determines when a household (or other entity) delists a house that has not sold | 5% probability each month after third month since listing. |

**Table 3 Parameter values used in base model runs**

| Parameter | Description | Value |
|---|---|---|
| **Empirical households per agent** | Degree of scaling of empirical data to agents in model to conserve computing resources | 10 |
| **$\gamma$** | Growth factor of permanent income | 1.02 |
| **$\kappa$** | Permanent income shock | Lognormal with $\mu = 0$ and $\sigma^2 = 0.168$ |
| **$\eta$** | Transitory income show | Lognormal with $\mu = 0$ and $\sigma^2 = 0.353$ |
| **RC** | Refinance cost | $5000 |
| **CC** | Closing costs | $0 |
| **MU** | Initial seller markup | U(1.0, 1.07) |
| **MD** | Seller periodic markdown fraction | U(0.965, 1.0) |
| **MDF** | Seller markdown frequency | U(1, 3) integer |
| **P(d)** | Probability of delisting | 0.05 |
| **a** | "Appreciation effect" used by buyers when determining how expensive a house to purchase | 0.17 |
| **b** | "LTV effect" used by buyers when determining how expensive a house to purchase | 0.05 |
| **$\varepsilon$** | Agent heterogeneity parameter in determinig desired expenditure | U(0.9, 1.1) |
| **$\tau$** | Fraction of house value spent each year on taxes, insurance, and HOA | 0.025 |
| **c** | Fraction of house value spent each year on maintenance | 0.025 |
| **mpc(I)** | Fraction of income spent each month on consumption | 0.6 |
| **mpc(w)** | Fraction of wealth spent each month on consumption (in addition to spending from income) | 0.025 |

Figure 29 compares the historical Case-Shiller index for the Washington DC MSA to the model derived house price index, rescaling so that both indices have the value of 1.0 in 1997. A quick look shows the house price model does fairly well capturing the first order dynamics of the crisis. Both indices gradually rise in 1997 and then move sharply up in the early 2000s before peaking late in 2005 and tailing off. However, there are some differences in the two graphs as well. The modeled output starts more gradual than the empirical output and also has a steeper slope from 2002 to 2005 to "catch up." The crash happens at about the same time for both graphs, but the empirical crash is larger and there is also an uptick towards the end of the empirical run that is absent in the model run.

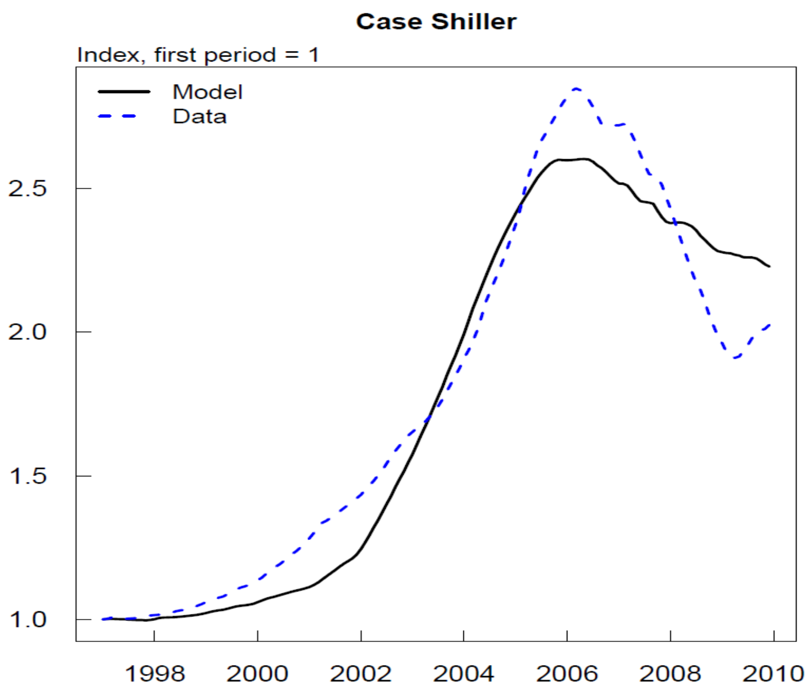


**Figure 29 Comparison of the empirically estimated Case-Shiller index for the Washington DC MSA to the model computed house price index. Empirical data derived from CoreLogic Case-Shiller index.**

Next, we can drill deeper into some of the intermediate outputs. Figure 30 compares the sale price of houses between the model and historical data. On the left side, the average monthly price shows a similar comparison as the house price index comparisons in Figure 29 during the bubble, but during the crash the average sale price is significantly lower in the model. This suggests that households in the model were more likely to switch to lower quality houses during the crash rather than drive down prices of existing houses when compared to historical data. This explains how the house price index fell less in the model run than in the historical data even though the average sale price fell much more in the model run. A future improvement to the model might make households' preferences for house quality dependent on the quality of house previously owned (for example due to family size or expectation of the housing crash reversing). This would temper the downward movement in average sale price in the model while increasing the drop in house price index. On the right side, the total distribution (encompassing all 13 years of the model run) compares quite well between model and data. The model does have more sales of cheap homes (and more sales overall) matching the observation earlier in this paragraph.

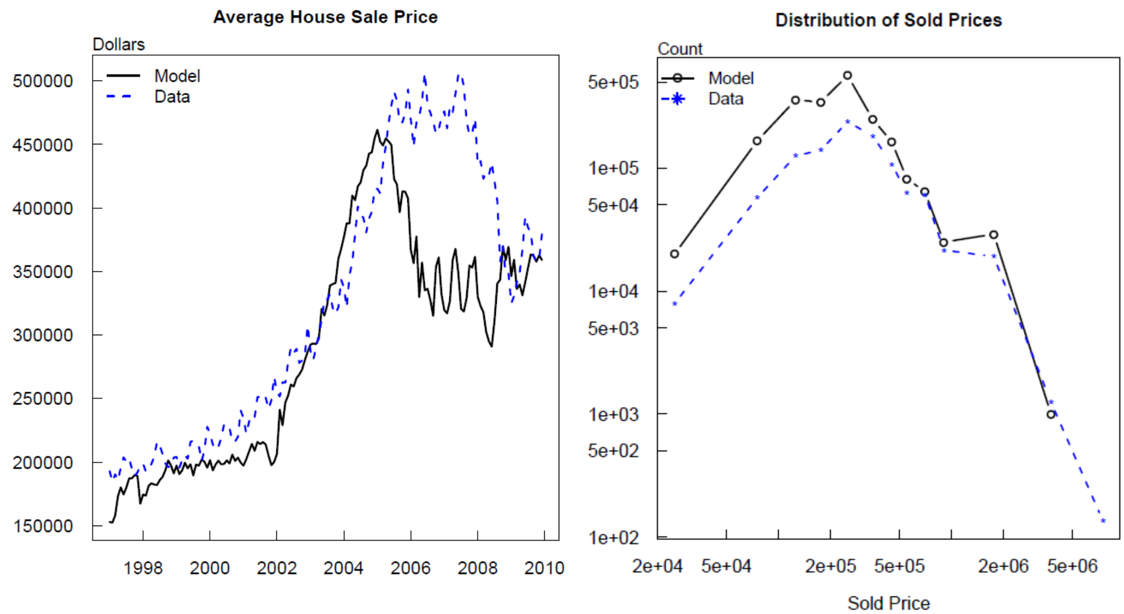



**Figure 30 Comparison of house sale prices (average and distribution) between historical data and the empirical model. Empirical data derived from data provided by the Washington DC Multiple Listing Service.**

Figure 31 presents outputs that dive deeper into how well the housing market model replicates key empirical housing market dynamics. Days on market describes the average number of days a house is listed before being sold. Of course with a one month time step, the housing market model's precision with respect to this variable is limited. However, the model does a good job capturing the general trends in this variable. During the height of the bubble (2002 – 2004), both the housing market model and the empirical data bottomed out and then rose as the bubble burst. Similar to the previous two figures, days on market continues to worsen during the later years of the simulation, whereas in the empirical data, the market had a slight rebound. Sold price to original listing price (OLP) has a similarly good fit as days on market. The last two curves in Figure 31—homeownership rate and units sold—have weaker matches to historical data, but in general both show the appropriate trend direction, although magnitudes are a bit off. Whereas the results in Figure 31 do not show perfect fits of the data, they also show off the power of ABMs. ABMs match deep structural dynamics of the market, such as shortened times on market, less price markdown, and higher quantity, that led to the housing price bubble. Conventional mathematical economic models typically only match a few variables and do not replicate key market dynamics.

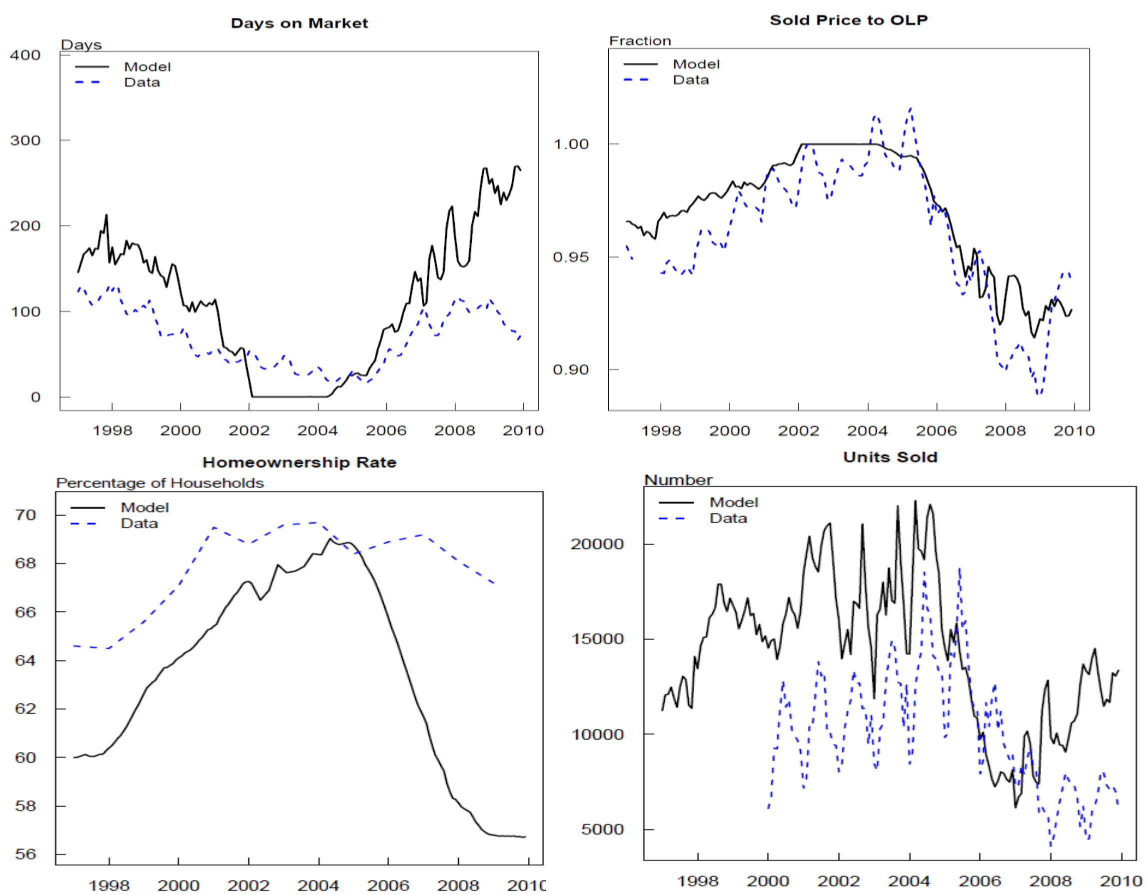



**Figure 31 Comparison of real estate market outputs between historical data and the model. The housing market model matches the trends in the historical data, illustrating how well the model replicates actual housing market dynamics. Empirical data for homeownership rate obtained from the Housing Vacancy Survey. Empirical data for the other three variables derived from data provided by the Washington DC Multiple Listing Service.**

Figure 32 presents loan characteristic output. Recall that central to many hypotheses regarding the origins of the housing market bubble are leverage and refinance made possible (and incentivized) by falling interest rates. Figure 32 indicates that the housing market model matches empirical leverage and interest rate movements quite well. This result enables the exploration later in this chapter regarding how things might differ if leverage and interest rates followed a different historical course. Note that, although the model uses input on leverage and interest rates in its model logic, endogenous activity in the model affects the actual leverage and interest rate of loans. For example, for each loan application the model draws an LTV, loan type, and interest rate from empirical data. However, the interest rate is drawn dependent on income and loan type, meaning that if the income of buyers in the model is systematically different than the income of buyers in empirical data, the actual distribution of loan interest rates in the model might diverge from empirical data. Similarly, the choice of LTV is drawn dependent on desired expenditure (which depends on income), and the actual pre-approved LTV might change due to the amount of buyers' liquid wealth. The outputs in Figure 32 show that the selection of buyers in the model is not systematically different than from historical data.

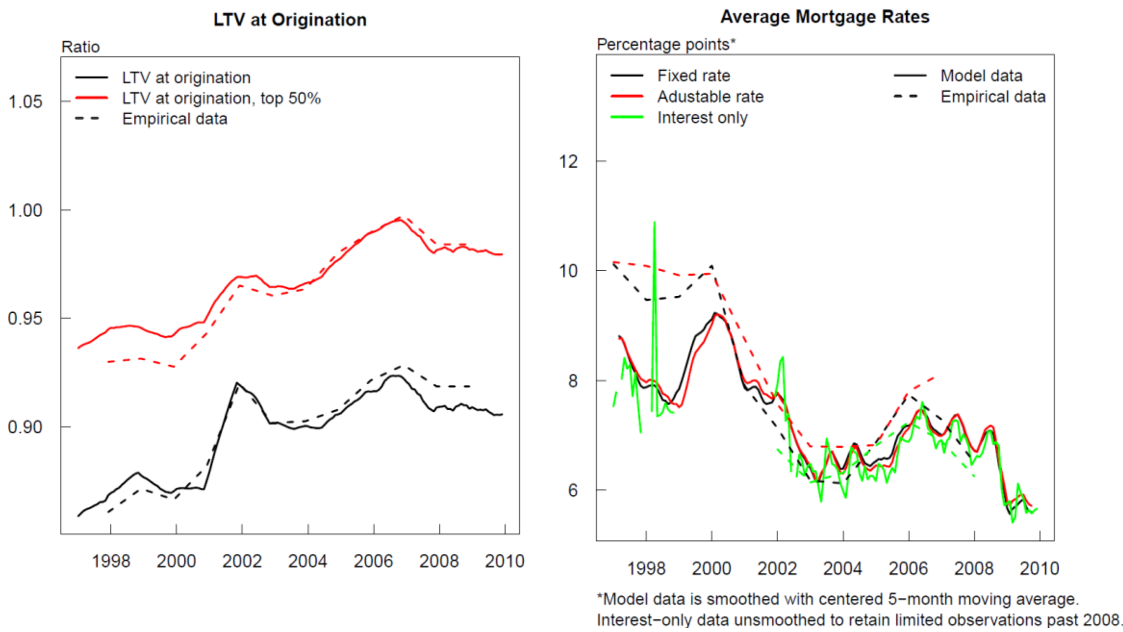
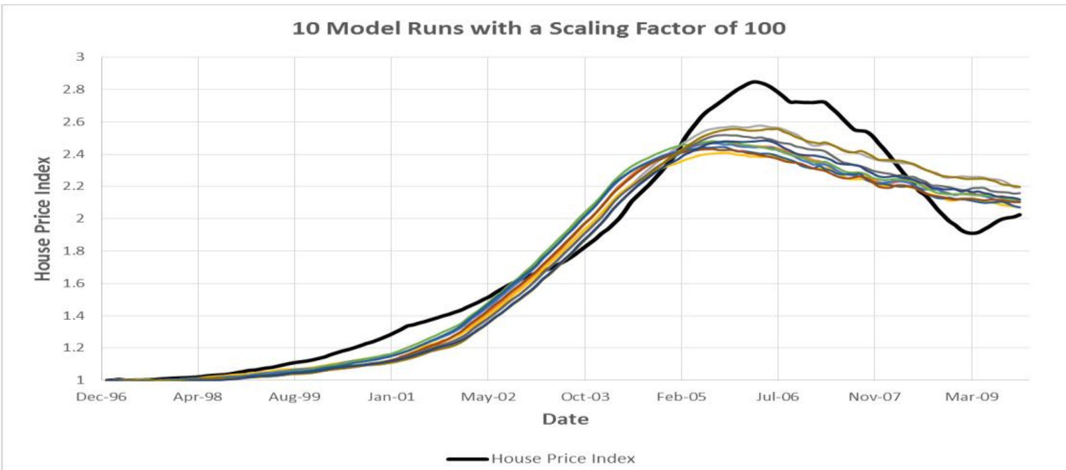



**Figure 32 Comparison of loan characteristics between model and empirical data. The loan characteristics for the housing market model match empirical loan characteristics well. Empirical data derived from LoanPerformance data, re-weighted to approximate the actual proportion of prime and subprime loans.**

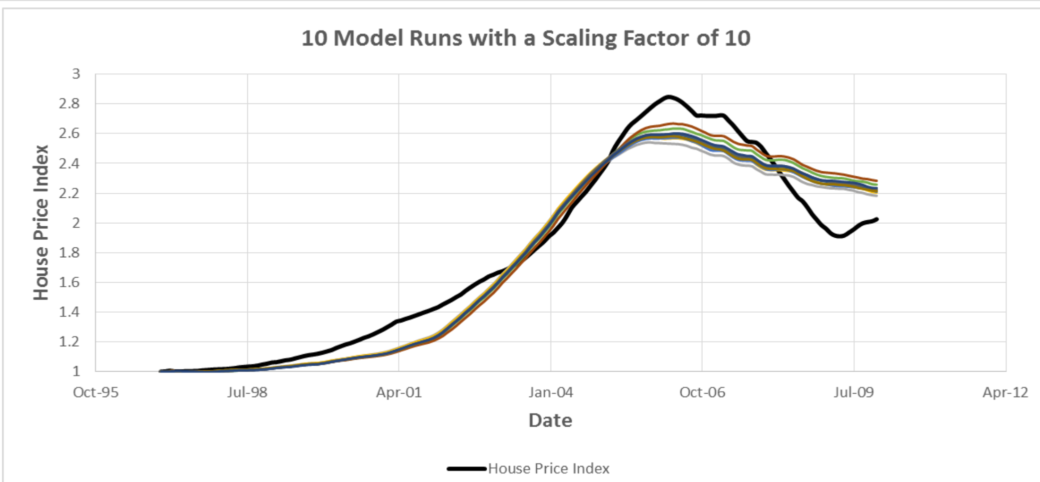
## 4.2. Run to Run Variation and Number of Agents

The run analyzed in the previous section included one agent for every ten actual households in the DC MSA, i.e., the model scaling factor is 10 to 1. There are around 2 million households in the DC MSA, meaning the simulation ran with about 200,000 agents. The question of how many agents to include in the simulation trades off run to run variability with computational efficiency. For example on a standard laptop (circa 2016), a single run of the housing market model with 200,000 agents requires around 12 minutes (note that the simulation is not multi-threaded so a single laptop can run multiple simulations at once). Moreover, the particular algorithm used to match buyers and sellers in the model scales quadratically—i.e., is $O(n^2)$—with the number of agents so altering the number of agents has a large effect on speeds. For example, running with just 20,000 agents requires less than one minute. In this section, I compare model results and run to run variability based on the number of agents in the model.

First, to gain some intuition in run to run variability, Figure 33 displays the house price index for 10 runs each for scaling factors of (a) 100 and (b) 10.




(a)




(b)

**Figure 33 Run to run variation for scaling factors of (a) 100 and (b) 10. Think black line shows the empirical Case Shiller index obtained from CoreLogic ([http://www.corelogic.com/products/corelogic-case-shiller.aspx](http://www.corelogic.com/products/corelogic-case-shiller.aspx))**

On both graphs, I overlay the historical Case-Shiller index in black, again rescaling all indices to a value of 1.0 for January 1997. For all 20 runs, the general result obtained in Figure 29 holds: the model generally reproduces a bubble and crash but does not match the historical data exactly. Moreover, the graphs for scaling factors of 100 and 10 seem similar, although the graphs at scaling factor 100 seem to peek slightly earlier. Another difference between the two charts is the run to run variance, which is generally low in both cases, but noticeably lower for a scaling factor of 10.

Next, I look at a more precise quantification of the relationship between scaling factor and run to run variability. For each individual simulation run, I compute a summary metric that quantifies how well the run matches historical data using the house price index output. Specifically, I compute a run's goodness of fit as:

$$fit = \sum_{m=1}^{M} (HPI(m) - CS(m))^2 \tag{8}$$

In the equation above, $M$ is the total number of months in the simulation which ranges from January 1997 to December 2009 (i.e., $M$ = 156), $HPI(m)$ is the model produced House Price Index at month $m$, and $CS(m)$ is the empirical seasonally adjusted Case-Shiller index for the DC MSA in month $m$. Again both the $HPI$ and $CS$ time series are rescaled so that $CS(0) = HPI(0) = 1.0$. Note that the lower the value of *fit*, the more closely the model reproduces the Case-Shiller index. For each scaling factor considered, I ran 100 simulations and computed the *fit* metric. The variance in this fit metric summarizes the run to run variability of the simulation at a given scaling factor.

Table 4 illustrates how scaling factor trades off between simulation runtime and goodness of fit and run to run variability. In each row of the table, I ran the simulation 100 run times to compute statistics for fit. The table confirms the intuition from Figure 33 that a lower scaling factor reduces run to run variation and improves fit. However, even at a scaling factor of 100, fit is almost as good as with a scaling factor of 5, and variance of fit is quite low.

**Table 4 Summary statistic for average fit, run to run variability, and average run time of the House Price Model for different scaling factors.**

| **Scaling Factor** | Approx num agents | Approx Run Time | Mean Fit | Variance Fit |
|---|---|---|---|---|
| **5** | 400,000 | 33 minutes | 3.57 | 0.005 |
| **10** | 200,000 | 12 minutes | 3.56 | 0.011 |
| **25** | 80,000 | 3 minutes | 3.66 | 0.053 |
| **50** | 40,000 | 85 seconds | 4.00 | 0.153 |
| **100** | 20,000 | 40 seconds | 4.27 | 0.494 |
| **500** | 4,000 | 10 seconds | 9.17 | 18.68 |
| **1000** | 2,000 | 7 seconds | 16.17 | 90.69 |
| **10000** | 200 | 5 seconds | 74.20 | 1568 |

Furthermore, mean fit does not improve when reducing scaling factor from 10 to 5, and variance of fit—although it does decrease between scaling factors of 10 and 5—is already miniscule when running at a scaling factor of 10. This suggests that running large scale analyses with the model, such as sensitivity analyses or output optimizations, can be run with a scaling factor of 100 without much degradation in model function. This result is especially useful given that the run time for a 100 scaling factor is several orders of magnitude faster than a scaling factor of 5. Note that the run time column is approximate and computed on a standard 2016 laptop. The runtimes illustrate the tradeoff between running the simulation with more agents. No particularly focused effort was made to improve runtime performance, and undoubtedly the simulation would execute faster with some performance tuning or better hardware.

## 4.3. Counterfactual Exploration

Agent-based models are well-suited for counterfactual analysis. Because these type of models both consume large amounts of data and model structural properties of a system, it is natural to use these models to explore what might have happened under alternative policies or cultural norms. For example in the introduction, I listed a number of possible causes of housing crises, which included excessive household leverage, low interest rates followed by an increase in interest rates, cash out refinancing, expectations, large capital inflows, and poor lending standards. A number hypotheses combined these fundamental causes. For example, Khandani et al.'s (2009) ratchet effect paper describes how low interest rates and lower lending standards (or as they put it, "near frictionless refinancing opportunities") enabled high leverage through cash out refinancing. In this section, I investigate a number of these hypotheses in the context of the Washington DC MSA using the housing market model.

The first hypothesis I investigate is the notion that Federal Reserve interest rate policies played a large role in the housing bubble and subsequent crash. One reason for this hypothesis is the temporal coincidence of the housing bubble with interest rate changes. Figure 34 plots the national seasonally adjusted Case-Shiller index (normalized so that January, 2000 = 1.0) against several key rates. Federal Reserve policy sets the fed funds rate, and this graph shows a steep drop in that rate during the key bubble years of 2000 – 2004, followed by a steep increase from the middle of 2004 to 2006, just before the housing crash. The mortgage prime rate, which keys off the fed funds rate, follows a similar but more muted path. Due to the relationship in timing of interest rate changes and market movements, interest rates factor into many narratives regarding the bubble, especially in the media but also in academic papers. However, the mechanism by which interest rates affected market movements differs in many accounts.

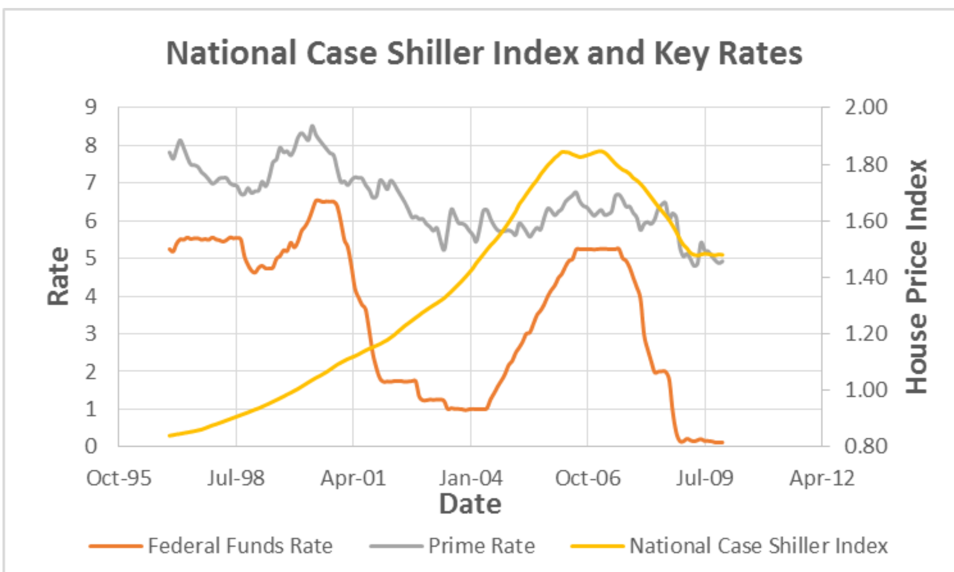



**Figure 34 National Case Shiller-Index plotted against the Federal Funds Rate and Mortgage Prime Rate. Case Shiller Index obtained from CoreLogic. Prime rate obtained from Freddy Mac. Federal Funds Rate obtained from Federal Reserve.**

One straightforward way rates can affect the market is through their effect on the money borrowers pay each month. For example, a borrower with a fixed rate loan of 8% on a $270,000 mortgage pays about $2,000 each month in payments, whereas a borrower with a 4% loan can acquire a $420,000 fixed rate loan for the same $2,000 monthly payments. Of course, the borrower with the $420,000 lower interest rate loan would need to either take on more leverage or make a larger downpayment than the $270,000 borrower (and other items such as taxes would be higher). Even so it is clear that reducing interest rates can significantly increase the house size some borrowers can obtain. In general, however, this simple narrative is not enough to explain the large price swings observed in the housing market, and most discussions of interest rates focus on it as a trigger in a more complicated process.

In Khandani et al. (2009)'s model of the housing bubble and crash, declining interest rates are one of the three key factors producing the refinance ratchet—the other two being rising home values and the ease of refinance. Combined, these three factors incentivize homeowners to repeatedly refinance their homes and extract equity. Thus, homeowners continually increase leverage, and once home prices stop rising, there is no analogous process homeowners can undertake deleverage, causing defaults. Because homeowners ratchet up leverage during the price appreciation period, defaults exhibit a higher than historically typical correlation during price declines, leading to a large market crash.

Gorton (2008) describes a more intricate, but somewhat related process in which refinance figures heavily into the bubble period, but once house prices stop rising the process stalls causing a tremendous crash. Gorton focuses specifically on subprime loans and describes that these loans are structured to force homeowners to refinance after two or three years. Typically, subprime loans are ARM loans with low teaser rates and high step-up rates after the initial teaser period. Borrowers can likely pay the teaser rates for a few years but not the higher rates after the initial teaser period and so must refinance after a few years. Moreover, these loans were often lent with very low downpayment requirements (recall from Chapter 2 that in 2005 nearly half the loans in the DC MSA required no downpayment). Therefore, the ability to refinance depended on whether house prices had increased and once house prices did not increase in early 2006, these homeowners defaulted. Gorton's description then moves into the shadow banking sector where he describes how these defaults, new derivate indices that revealed more information about the shakiness of the market, and the opaque nature of mortgage-backed securities led to a general distrust of all mortgage-backed securities. That distrust reduced the value of these securities, damaging balance sheets, and shutting down much of the lending capital to the housing market. With less lending capital, loan standards tightened causing a crash in house prices.

In both the Khandani et al. (2009) and Gorton (2008) accounts interest rates play one or two roles. First, they incentivize refinance which both authors view as a key part of the engine that ran up house prices. Second, both authors describe the crash as magnifying an initial small dip in house prices. Although neither author pins this small dip on increased interest rates, it is not hard to see that although rising interest rates would not in themselves produce a huge price drop, rising rates can easily produce a small drop that could set off either of these mechanisms.

Although the housing market model does not contain all the intricacies of the shadow banking sector in Gorton's theory, it does contain all the elements of Khandani et al.'s theory. Moreover, Gorton's theory relies on house price appreciation during the bubble period—although he does not conjecture the source of this appreciation—and if the Fed never lowered interest rates, that appreciation might never have occurred. Thus, although not a perfect test, running the model with interest rates stable at January, 1997 levels would still reasonably test Gorton's hypothesis.

Figure 35 displays the results of a run of the house price model with the mortgage prime rate kept stable at its January 1997 level of 7.6%. Each graph shows the actual historical data, the "base case" run of the model (the one presented earlier in this chapter), and the counterfactual run. The base case is the same run analyzed earlier in this chapter, and both model runs use a scaling factor of 10. Panel (a) shows that keeping interest rates constant mutes the housing bubble, but does not completely eradicate it. Similarly the crash is now a small, steady decline. Note that house prices still shoot up by around 60% over the course of about 4 years. Because DC experienced a relatively minor crash compared to cities like Las Vegas, it is not clear whether holding interest rates steady would in fact have averted the housing crash. However, the results seem to show that although the bubble was not solely caused by interest rates, holding interest rates steady could have alleviated the crash. This lends support to Gorton's and Khandani et al.'s theories. Other panels support this general story. Panel (b) shows a sharp increase in average house price—but more moderate than historical and base case runs—and almost no subsequent decline in house prices.  Note that panel (b) is smoothed over 11 months to better show trends.

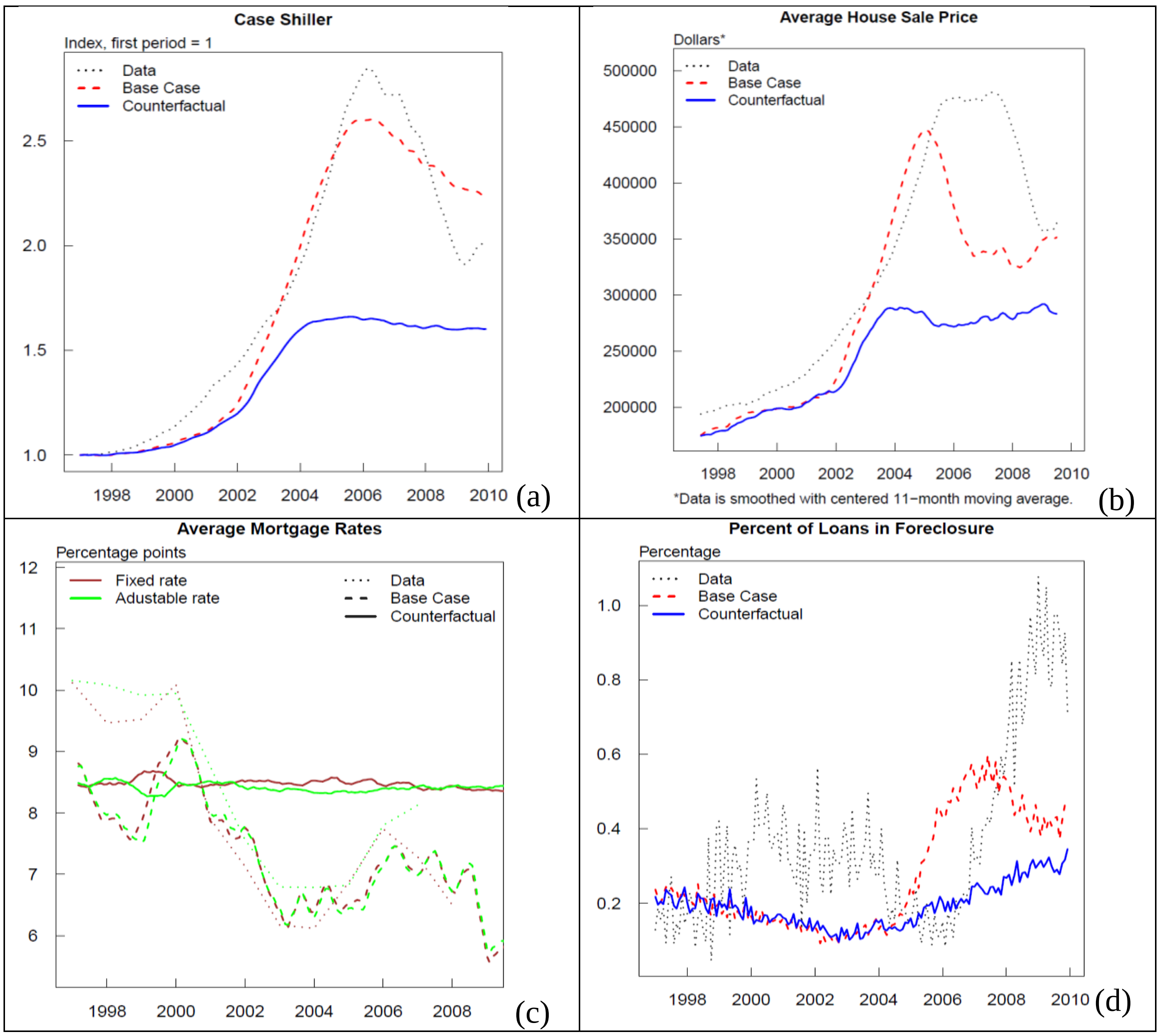


**Figure 35 Results for stable interest rate counterfactual.**

Panel (c) confirms that rates for both fixed and ARM loans remained constant throughout the simulation (i.e., this plot was included to confirm we did in fact run a counterfactual that fixed interest rates). Finally, panel (d) shows that the counterfactual run had fewer foreclosures than the base case run. However, in the counterfactual run, foreclosures are on the rise at the end of the run, whereas in the base case, foreclosures are dropping. This suggests, that perhaps a crash is coming in the counterfactual run, after the end of the simulation.

Household leverage also figures centrally into most—nearly all—hypotheses about the housing crisis. In fact, even Gorton's and Khandani et al.'s theories have a leverage component, due to cash out refinancing (although in Gorton's case, he is not specifically concerned with cash out refinance, but rather the refinance motivator is really interest rates). Geanakoplos' (2010) leverage cycle theory has been applied to explain the housing crisis. In this theory, the most optimistic potential owners of an asset obtain the asset during good times since they are willing to pay more and take on more leverage. Since times are good, these optimistic buyers profit the most and can afford to buy more of the asset, such that at the top of the leverage cycle, the asset accumulates in the hands of the most optimistic buyers who are also the most levered. When something—such as unanticipated bad news—negatively shocks the market, those optimistic buyers lose out and have to liquidate the asset especially since they are so highly levered. The asset then falls to the more pessimistic potential owners who value the asset less and the price plummets further fueling a crash in price and transfer of the asset to pessimistic owners.

One way to test whether leverage did in fact play as crucial role in the housing market crisis as argued in many theories is to simply hold levels of leverage fixed over time. Recall from Figure 7, mean LTV of new loans increased from 86 to 93 from 1997 to 2006, and about half the loans originated in 2006 required no downpayment. To test whether this rise in household leverage was central to the housing crisis, I ran two counterfactuals: (1) all loans required at least 10% downpayment (i.e., LTV at origination was always less than or equal 90) and (2) all loans required at least 15% downpayment.

Figure 36 shows the same graphs as Figure 35, except replacing Panel (c) with a graph of LTV at origination. In both counterfactual cases, the top 50% of loans all hug the LTV maximums, and the early 2000s still show some jump in average LTV, but of course much less than in reality or in the base case run. Figure 36 shows that, according to the model, keeping leverage stable does in fact prevent both the bubble and the crash, but only at the draconian policy of a minimum 15% downpayment. At a slightly softer policy of maximum 90 LTV, prices still rise by around 60% during the bubble period, but there is no crash (similar to the stable interest rate counterfactual). Foreclosures are improved versus the stable interest rate policy in both counterfactual cases. In fact, the housing market exhibits no drop in prices and shows a gradual rise in prices and price index at the end of the simulation. Thus the LTV counterfactuals seem to leave the housing market in a better state at the end of the simulation than the interest rate counterfactual.

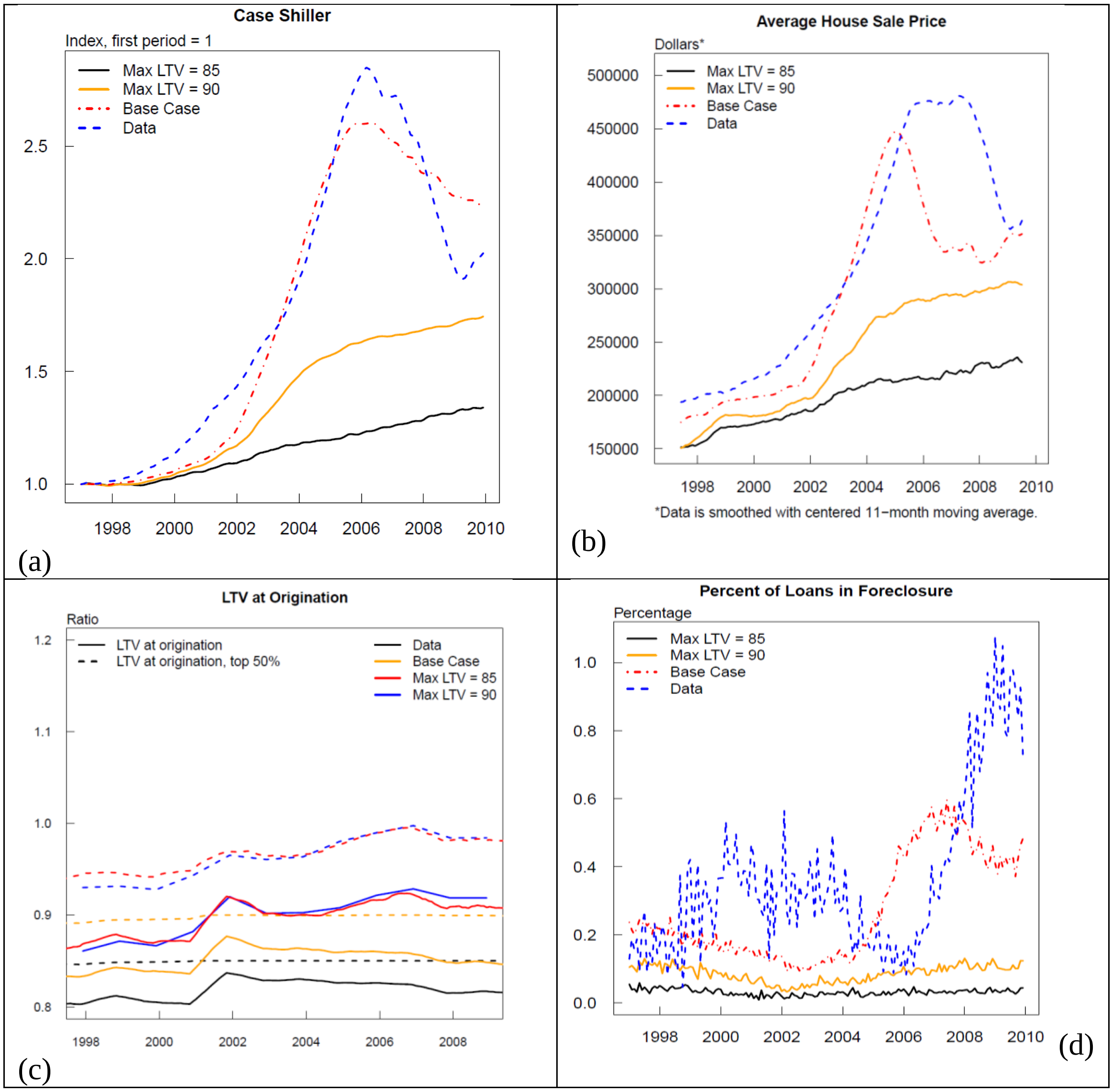



**Figure 36 Results for stable leverage counterfactual.**

Note that the average house sale price at the beginning of the simulation is lower for these two counterfactual runs than the base case. The reason for this is that as part of the model initialization, there is a "burn-in" period before 1997 in which the model runs for a number of time steps (equivalent to 100 years in the runs in this dissertation) with the 1997 settings to eliminate initial transients and reach a steady-state that exhibits correlations (e.g., between wealth, income, and household owned) representative of reality but not directly presented in our data sources. The initialization period adheres to the LTV constraints and thus the steady state distribution at the end of this initialization contains a somewhat lower distribution of house prices. In the graph below, the average house price of the base case run for January 1997 is around $175,000, but only about $150,000 when LTV is constrained.

None of the three policy alternatives investigated—stable interest rates, stable leverage at maximum of 90 LTV, and stable LTV at a maximum of 85 LTV—quite solved the housing crisis. Keeping leverage stable at a maximum of 85 LTV did largely prevent the bubble and crash, but this policy is quite restrictive and unlikely to be implemented in the real world. The 90 LTV and interest rate counterfactuals both muted the bubble and crash, but neither eliminated all aspects. Another reasonable alternative is to combine the stable interest rate policy with the policy limiting LTV to be no more than 90. Figure 37 presents the results of this combination. Panel (a) shows that the Case-Shiller rises more or less steadily rather than including any sudden rises or drops. The trend is slightly faster than inflation, but still reasonably moderate. Panels (c) and (d) show that the housing market is healthier with the combined policy. Homeownership rate is higher and foreclosures are lower at the end of the simulation than for the base case or the individual policies.

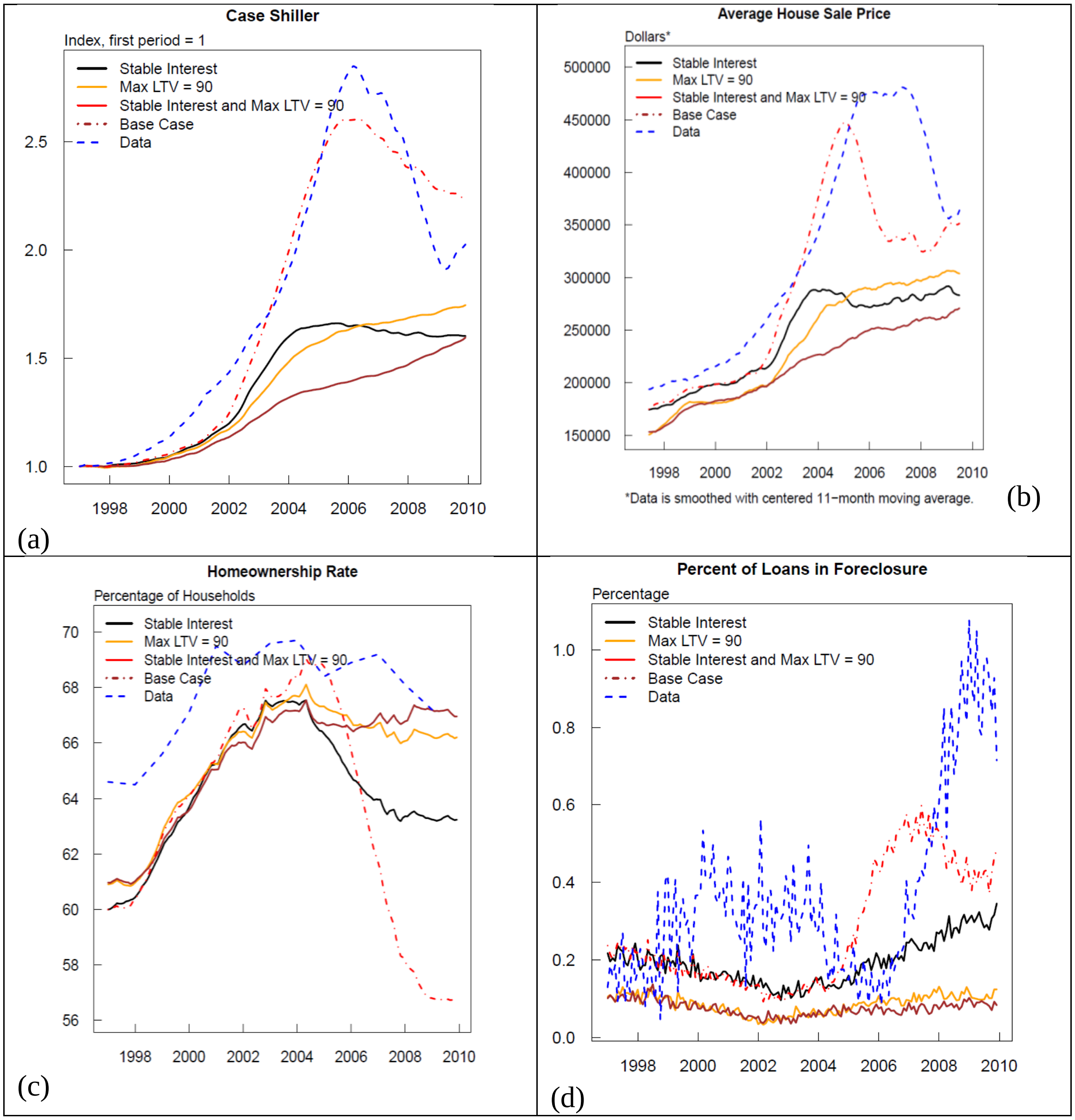


**Figure 37 Results for stable leverage and interest rate counterfactual compared to each policy individually**

A simpler policy alternative that, according to both Gorton's and Khandani et al.'s theories, should have prevented the housing crisis would be to eliminate refinance. Although this policy would not be practical because it would incentivize households to move whenever rates dropped, it is interesting to consider for the purposes of evaluating

Gorton's and Khandani et al.'s theories. Two alternative policies can be considered: (1) prohibit any type of refinance or (2) prohibit cash out refinancing—i.e., any refinance in which the new loan's principle is greater than the old loan's.

Figure 38 displays the result of both of these interventions, and both show almost no influence on simulation outcome. Panel (c) describes the number of refinances as a percentage of all loans each month. This chart makes several things clear. First, there are very few cash out refinances in the model, which suggests an avenue for model improvement in the future. Second, eliminating rate refinancing has almost no impact.

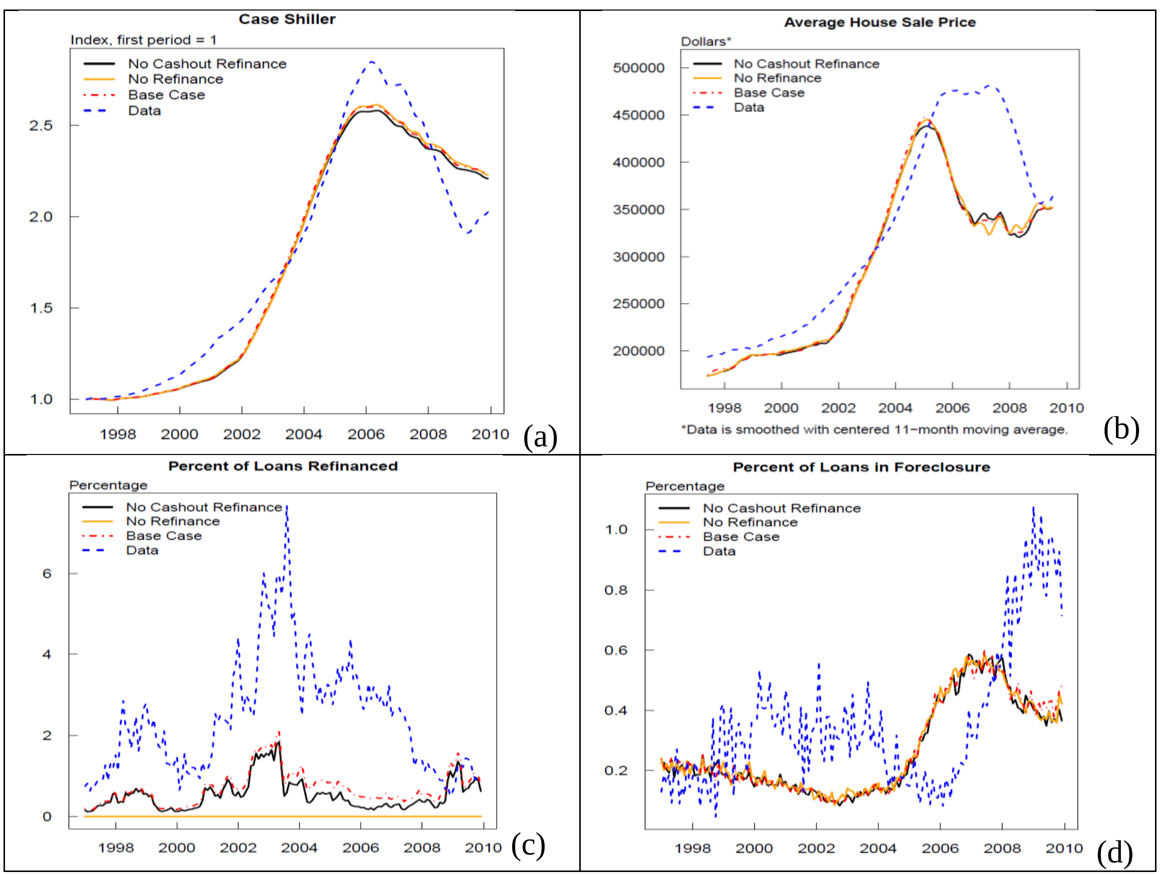



**Figure 38 Results for no refinance and for no cash out refinance counterfactuals**

Beyond the theories about leverage, interest rates, and refinance, other theories focus on lending standards, loan types, and expectations. For example, Mian and Sufi (2009) argue that the housing bubble was caused by expansion of credit to less credit-worthy borrowers ("subprime" borrowers) leading to an increase in housing demand that drove up prices. At the same time, this increase in demand came from the riskiest borrowers also increasing the riskiness of mortgage-backed securities. This is essentially the argument from Duca et al. 2011 who pair weakening credit standards with innovations in mortgage backed securities (MBS), such as traunching and credit default swaps, as primary in both the bubble and crash. Unfortunately, this aspect of the model is not highly developed. There is no model of the banking sector, and also we do not model households lying on their loan applications. For example, when the model computes a desired expenditure or tries to get a loan with a particular LTV and DTI, the model uses the household's true wealth and income. Therefore, it is somewhat difficult to model some of the interventions that might address these causes. Moreover, the LTV counterfactuals somewhat addressed these concerns. Since we do not have direct knowledge of who "subprime" borrowers are, a good proxy for them would be households with low wealth and low income. By requiring at least a 10% downpayment, low wealth households are excluded from the market. Moreover, the 10% downpayment protects against strategic default because it ensures that household have some equity cushion at purchase.

Similar to LTV maximums at origination, another proxy for reducing subprime borrowing is to eliminate adjustable rate mortgages. Many homeowners opt for ARM loans because the teaser rates make monthly payments more affordable for the first few years of the mortgage. After those teaser years, homeowners can refinance into a new loan, sell their house, or pay the higher rates with a higher income. Each of these scenarios requires the homeowners' situation to improve in some manner—either house price appreciation or income increase. Because the probability none of these occur is not insignificant, risk of these loans is not insignificant. ARM loans and the necessity to refinance after the teaser period figures heavily in Gorton's (2008) analysis. Therefore, I ran a counterfactual in which households could only receive fixed rate loans, not ARM loans.

Figure 39 presents output for this counterfactual run, and according to the model, eliminating ARM loans would not have prevented the housing crisis. Panels (a), (b), and (d) show the Case-Shiller index, average house price, and foreclosures respectively, and in all cases, the counterfactual run produces almost no change from the base case. There is a slight mitigation of the housing crash, but not much. Panel (c) confirms that counterfactual run did, in fact, run with only fixed rate loans. That eliminating ARM loans has little effect on the crisis according to the model is not that surprising given how little restricting refinances affected the simulation. Most accounts—such as the Gorton account discussed previously—that place ARM loans at the center of the housing crisis typically also include refinancing as a necessary aspect of the housing crisis. Because the model ascribes little role for refinancing in the crisis, it is not surprising that ARM loans are also unimportant.

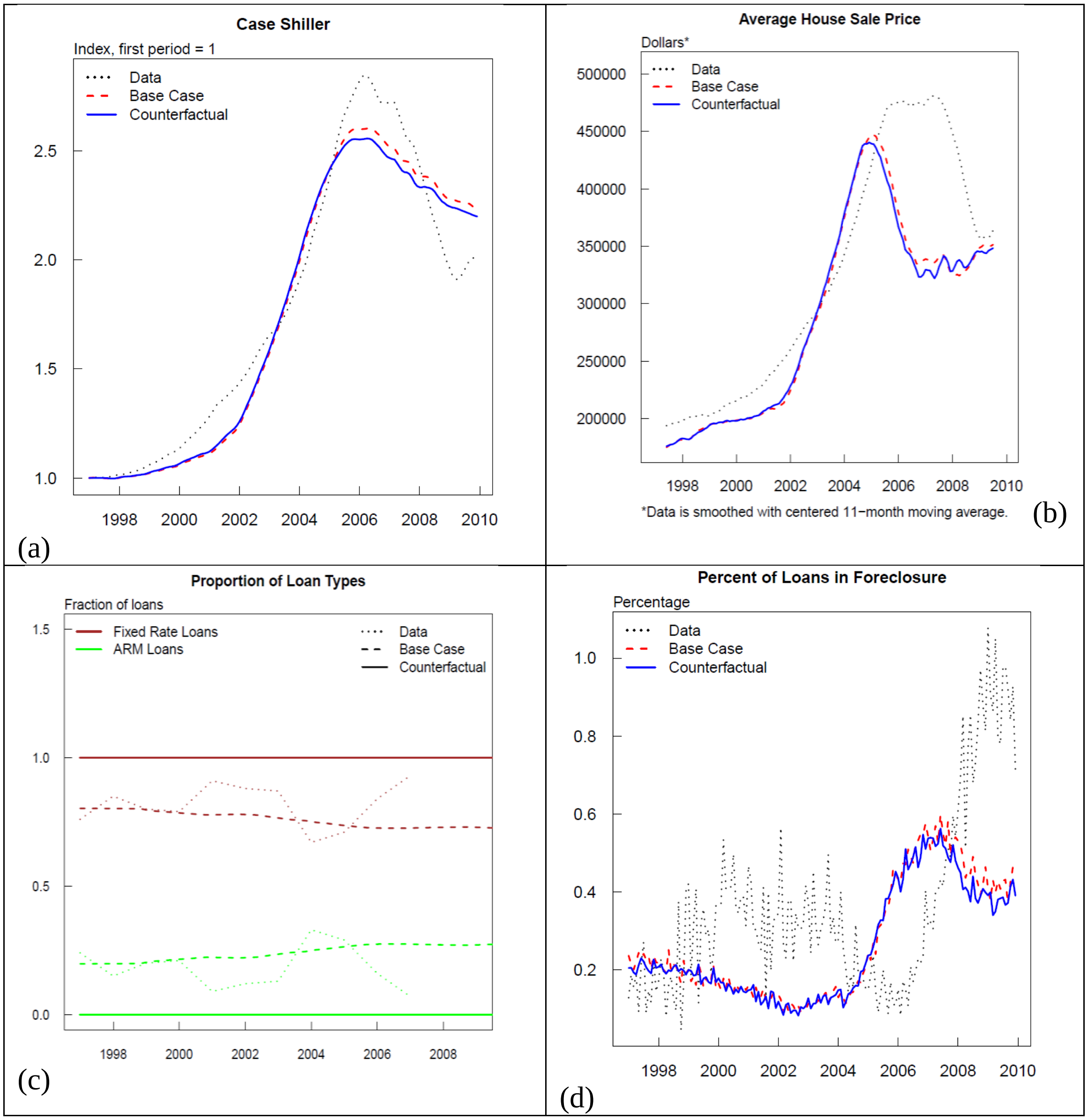



**Figure 39 Results for no ARM loan counterfactual**

Other theories of the housing crisis put less emphasis on policy failings and more emphasis on the, perhaps irrational, behavior of market participants. For example, Case and Shiller (2003) argued (in the midst of the bubble) that expectations of rapid, steady house price appreciation were motivating buyers to drive up house prices. They also noted that his situation is inherently unstable and cautioned that the bubble might burst soon—although it took a few years. The essential mechanism of their argument is that buyers price in their expectation of future house price appreciation and base this expectation on the current situation, including recent changes in prices and general sentiment of others. Because these expectations reinforce recent behavior—i.e., buyers price in recent appreciation to new purchases accelerating current trends—market movements are more pronounced than just fundamentals alone would dictate. This theory creates a cyclical dynamic that produces bubbles and crashes. More recently, Hott (2009) argued that fundamentals alone cannot explain housing price fluctuations, whereas expectation-driven behavior, such as herding, speculation, and momentum trading could.

Recall from Chapter 3 that a household's desired expenditure includes the term $a\delta(p)$ where $\delta(p)$ is the change in house price index over the last 12 months. The parameter $a$ controls the degree to which the past change in house prices influences the buyer's target purchase price. When $a$ is high, buyers drive prices even higher during boom times and drag prices down even lower during bust times because their desired expenditures reflect expectations that the current house price trend will continue. To test hypotheses about the role of expectations in the housing crisis, I ran several experiments with different settings for the $a$ parameter. For example, the $a = 0$ run simulates a counterfactual in which expectations play no part in house price determination. The base case run had $a = 0.18$. Figure 40 shows runs for six different values of $a$. When $a = 0$, house prices rise less steeply than the base case, and there is no crash. However, the price does rise rapidly, ending the simulation about 75% higher than at the beginning. Other metrics, such as homeownership rate and foreclosures, also look strong for the $a$ = 0 run. Similar to the Max LTV = 85 run, which eliminated the leverage cycles, eliminating expectation cycles also produces a healthier market (however, imposing downpayment requirements is a much easier policy to implement than eliminating households' expectations).

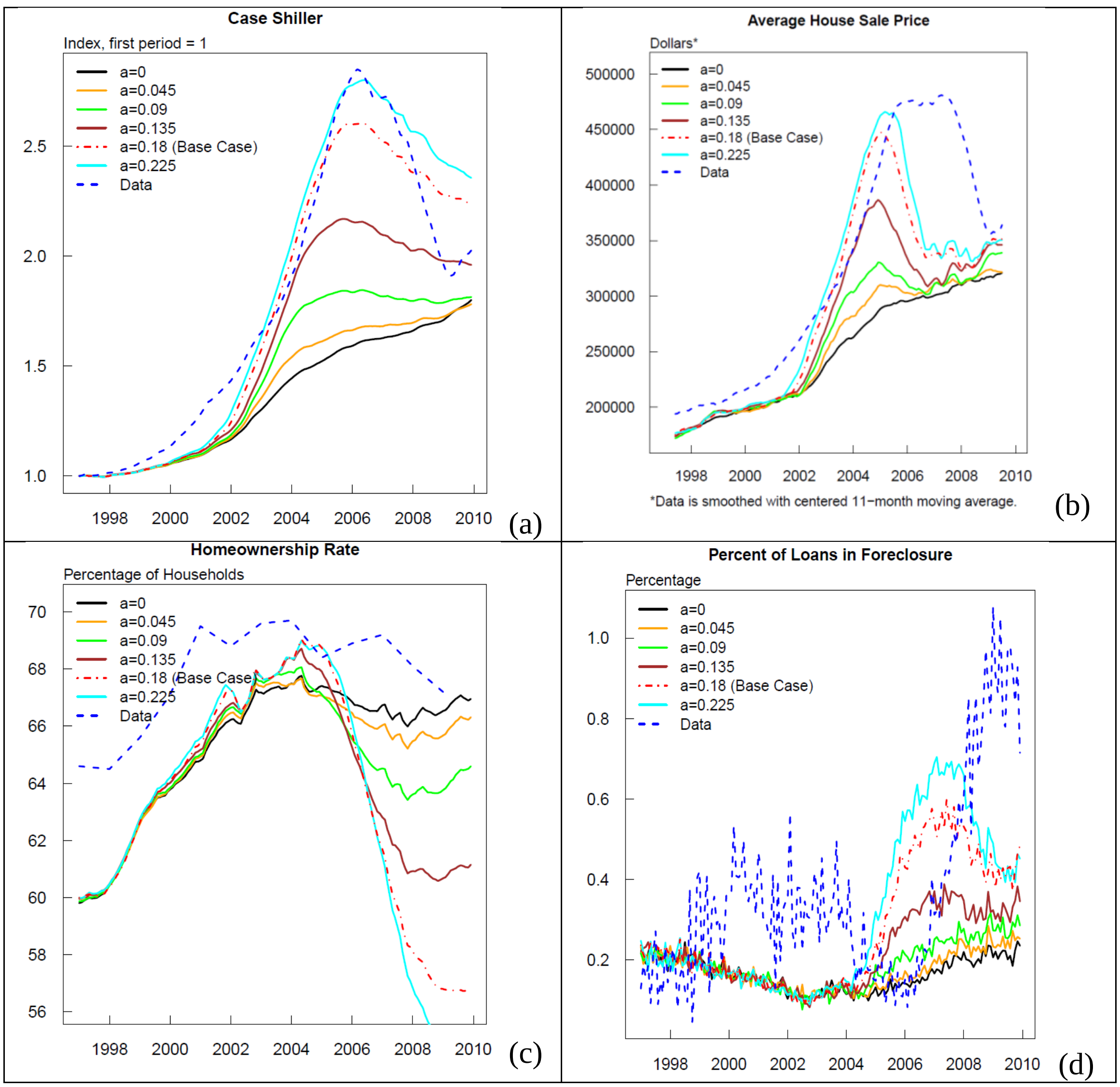



**Figure 40 Results for different values of the "a" parameter, which controls expectations**

Values for $a$ between 0 and 0.18 produce bubbles somewhere in between the ones produced by $a = 0$ and $a = 0.18$. Not surprisingly, $a > 0.18$ produces an even bigger bubble and crash than the base case, and other metrics, such as foreclosures and home ownership rate exhibit larger swings.

In conclusion, the counterfactual that produces the most desirable house price index curve is the one in which the maximum LTV for loans remains fixed at 85 for the entire simulation. However, this policy is rather draconian. A blend of more stable interest rates and a maximum LTV of 90 also produces a reasonable result. Importantly, expectations play a big role in the housing market gyrations, but they only explain some of the housing cycle, according to the model. Other elements, such as refinance and ARM loans had little effect on housing crisis, according to the model.

# 5. MODEL SENSITIVTY ANALYSIS

This chapter investigates the sensitivity of house price model results to variations in model parameters. In the previous chapter, I listed all the model parameters and agent rules used within the model (Table 2 and Table 3). This begs the question: how sensitive are model results to the precise values in those tables? I began to answer that question when I varied the *a* parameter during the counterfactual analyses. The *a* parameter controls the degree to which households factor expectations of house price appreciation or depreciation into their desired expenditures. Model results were somewhat sensitive to this parameter. For $a = 0$—i.e., expectations do not matter—the model produces less of a bubble and no crash. For $a > 0$, the model generally recovered the bubble and crash dynamic, but the fit of the output curves varied significantly with the choice of *a*. I did choose a wide range for *a* (from $a = 0$ to $a = 0.225$) so it is not surprising model results varied. In this chapter, I do a more systematic study of the parameters and rules used in the model to determine the ones to which the model is most sensitive. It turns out the *a* parameter is a sensitive parameter, but there are other parameters and rule choices whose values influence outputs more significantly. It is those parameters and rules that must be carefully calibrated and also sampled around when extracting conclusions from the model. One contribution of this dissertation is the demonstration of a sensitivity analysis that varies, not only parameters, but model rules as well (which I call a structural sensitivity analysis and discuss in more detail in Chapter 7).

## 5.1. Housing Market Model Background

For this chapter, I use a newer version of the housing market model than I used in Chapters 3 and 4. This model (see Axtell et al. 2014 for details) is qualitatively similar to the model in the previous chapters but was upgraded in the following manner:

1. The team replaced the LoanPerformance loan data with the more representative CoreLogic data.
2. The new model updates several of the behavioral rules. For example, strategic default incorporates an expectations component (i.e., not solely based on LTV), and the desired expenditure function is more nuanced. I go over some of these rules when I analyze sensitivities.
3. The upgraded model contains a few new aspects, such as a rental market and investors (i.e., households that could own multiple houses).
4. The team attempted to calibrate portions of the model, independent of the rest of the model. For example, using data on expenditures and income, the team tried to find the actual value of the *a* parameter that controls the influence of expectations. The team did this for a number of the rules, and I test the sensitivity of the model to these parameters to determine how important the accuracy of these calibrations are to the model results.

Although I do not delve into a description of the new model in as much depth as in Chapter 3 (again see Axtell at al. 2014 or see the rulebook created for that model at https://www.dropbox.com/s/a6okv9birl5ikqu/Master.pdf), I describe portions of the model in enough detail to present the analysis. Before doing so, it is important to establish a new base case.

Figure 41 presents results for a base case run of the new model. The results look worse than the model in Chapter 4, mainly because the team took a principled approach to calibration. In Chapter 4, parameters were hand tuned so that outputs looked good. Of course, the Chapter 4 model did have quite a bit of constraints, such as behavioral rules clamped to data (e.g., choice of LTV, income distribution, etc.), and the model matched not just a few outputs, but a number of the "intermediary" market phenomena, such as the ratio of sold price to original listing price and the distribution of house prices. Even so, hand tuning parameters based on model results provides modelers with too much freedom to make the model results look "good." The model in Chapter 5 uses parameters calibrated on data outside the model with little hand tuning, and consequentially the results looks worse. However, the model still produces a bubble and crash and tracks some of the model outputs well. Therefore, the model still recovers the essential features of the crisis and can be useful for exploration. In this new model, the bubble is more muted and it peaks later, whereas in the earlier model the bubble peaked slightly early. On this new model, Axtell et al. ran a few counterfactuals: stable interest rate, stable leverage, and stable interest rate + leverage. The results were generally similar to those in Chapter 4 with leverage being more influential than interest rates, but the combination producing the greatest impact. Axtell et al. also looked at the influence of the *a* parameter and also concluded the model was sensitive to changes in this value.

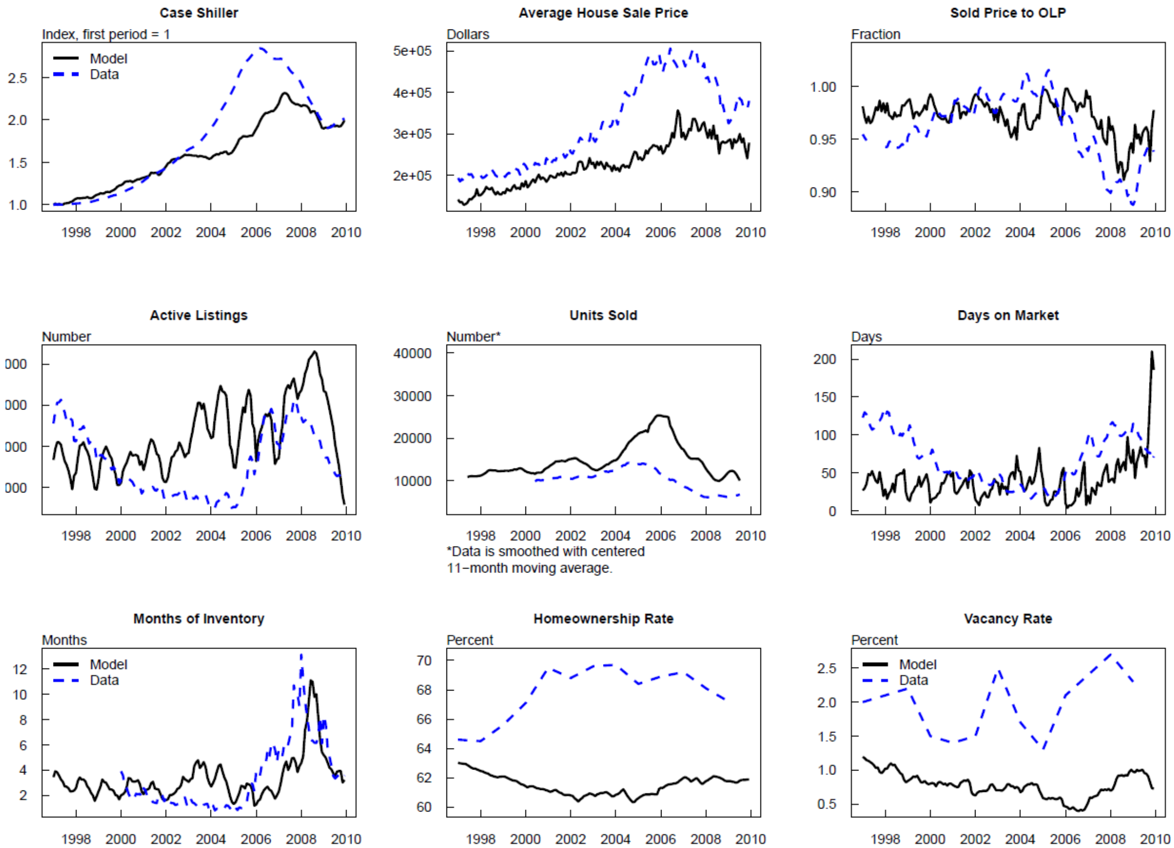



**Figure 41 Base case run for updated model**

## 5.2. Sensitivity Analysis Methodology

I performed a sensitivity analysis on some of the more important modules: desired expenditure calculation, approved leverage algorithm, seller list price algorithm, strategic default decision, and cash out refinance decision. Each of these areas contains behavioral rules either calibrated from data or defined from theory. In the case of data calibration, often the data is not a perfect proxy for the behavior in the model. For example, the team used actual expenditure data to calibrate the desired expenditure function, but actual expenditure data omits observations in which prospective buyers made no purchase. To the extent the distribution of desired expenditure for non-buyers versus actual buyers is different, the source data is biased. Moreover, the actual expenditure a household makes might be different than the household's desired expenditure. In fact, that is often the case in the model. Therefore, it is important to understand the influence parameters in the desired expenditure function have on model results to determine whether a future iteration of the model should attempt a new calibration.

For each run of the model, I use two measures of sensitivity. First, I use Equation (8) introduced in Chapter 4 to measure the degree to which the model-produced house price index deviates from the true Case-Shiller index. I call the value of this metric *fit*. I ran the base case 100 times and found the average base case fit, which I call $fit_b$ to equal 25.67.

Next, I use the maximum House Price Index (HPI) as a measure of the extent of the bubble. Note that in many previous graphs (including Figure 41), the House Price Index is scaled so that its value in the first month (January 1997) equals 1.0. For this metric, I do not perform this scaling in order to follow the suggestions for measuring bubble extent in Contessi and Kerdnunvong (2015). The authors suggest that a bubble exists when an asset's price grows faster than its fundamental value. One measure of fundamental value of real estate is the expected stream of rental payments, and in the housing market model, rental price is a function of house quality. Therefore, house quality is a proportionate to fundamental value and raw HPI (i.e., not scaled by HPI in month 1) describes the average ratio of house price to house quality. In other words, if raw HPI = 2.0, then on average the actual sold price of a house is twice its quality value.

Note that in the model, quality is proportionate to fundamental value. Since incomes and wealths rise over time, we expect HPI to drift upward. However, income and wealth are clamped to the same empirical data in all runs. Therefore, raw HPI is useful for comparing the bubbles of two runs (or comparing to historical data). If raw HPI is higher in one run versus another run, the run with the higher HPI has asset prices above fundamental value to a greater extent. I call the value of this metric *extent*. I ran the base case 100 times and found the average base case fit, which I call $extent_b$ to equal 1.71.

The combination of these two metrics (fit and extent) gives a more complete picture of sensitivity than a single metric. For example, if I use only the fit metric it is not clear whether, for example, a decrease in fit results from a smaller or much larger bubble because the base case run (see Figure 41) fits very well until 2003 and less well afterwards. Conversely, because the bubble extent metric only captures a single value (the maximum raw HPI), it will miss the effect of parameter changes to other aspects of the HPI curve, such as the crash portion or bubble timing.

I vary each numerical parameter and each rule one at a time. For numerical parameters I execute 200 runs, sampling the parameter value on the distribution U(0.5*x*, 1.5*x*) where *x* is the parameter value in the base case run. I produce a scatter plot of these runs to present a full, graphical picture of the sensitivity. In a few cases, it does not make sense to sample on U(0.5*x*, 1.5*x*), and I modify the distribution accordingly.

To compute statistics, I do the following. Let variable *x* be the variable of interest, $x_b$ be the value of *x* used in the base case, and $x_i$ be the value of *x* used in run *i*. For each run, I compute the following triplet: [$y_i$, $f_i$, $e_i$] where $y_i = \frac{x_i}{x_b}$, $f_i = \frac{fit_i}{fit_b}$, and $e_i =$

$\frac{extent_i}{extent_b}$. This produces 200 triples for a particular variable under consideration. I divide the triplets into two sets, those with values of $y_i < 1$ and those with values $y_i > 1$. Then, I compute a simple linear regression of $y$ on $f$ and another of $y$ on $e$ for both sets. This provides a sensitivity score for both the model fit and bubble metric for both increasing and decreasing the variable of interest. For rule sensitivities I simply do 100 runs with each rule combination and compare the average fit to $fit_b$ and the average bubble extent to $extent_b$. This provides a sensitivity for individual parameters and rules. Clearly, some parameters can have interactions, and it would be interesting to produce a more general analysis of the input space. I leave much of that work to future research, but I do produce one example to test the interaction of leverage and expectations. However, even without varying more than one parameter at a time, the work in this dissertation provides a number of interesting insights into sensitivities for the housing market model.

## 5.3. Desired Expenditure Module

The desired expenditure computation is heavily influential on the demand side of the model (the other main influence of demand being leverage level). The formulation for desired expenditure in the new version of the model is somewhat different than the Chapter 3 model's version. First, there are actually two different rules operating in the model: a log regression rule calibrated to CoreLogic data (which I call LogRegression) and an improved version of the desired expenditure rule described in Chapter 3, (which I call IncomeAndCosts). Half the agents follow each rule.

The LogRegression rule was estimated from 50,000 records that include both income and house expenditure and is simply a logistic regression of expenditure based on income:

$$D = HPI * \ 10^{2.498290+0.5565*log_{10}(income)} \tag{9}$$

*D* is desired expenditure; *HPI* is the house price index (used to scale desired expenditure to the current housing market); and *income* is annual income. Although this formula does not include a momentum factor such as the recent house price appreciation, it does include the current house price index within it. This could induce some momentum behavior (since as prices increases so does desired expenditure).

The IncomeAndCosts rule is an update from the rule described in Chapter 3

. The team estimated the parameters of this rule from national PSID data on 4346 samples:

$$D = \varepsilon * \frac{h * income^{g}}{(\tau + c + r - a\delta(p))} \tag{10}$$

Where

- $D$ is desired house price

- $\varepsilon$ is a parameter that models heterogeneity between agents (in the base case, log $\varepsilon \sim N(-0.1646, 0.4355)$)
- $h$ is a scaling factor and equals 34 in the base case.
- $g$ captures the amount of income spent on housing and equals 0.5782 in the base case.
- *income* is yearly income
- $\tau$ is taxes, mortgage insurance, and homeowners association fees (i.e., fixed non-mortgage expenses)
- $c$ is maintenance expenditure (i.e., discretionary non-mortgage expenses)
- $r$ is the prime rate for mortgages
- $a$ is the "appreciation effect" and governs how much a homeowner believes its house will appreciate or depreciate given recent history. $a$ = 0.08 in the base case.
- $\delta(p)$ is the change in house price index over the last 12 months, computed endogenous to the model.

For this analysis, I test the sensitivity of the $a$, $g$, $h$, and $\varepsilon$ (both $\mu$ and $\sigma$ of the lognormal distribution governing $\varepsilon$) parameters. Then I test the model's sensitivities to different frequencies of the two rules. Figure 42 presents the results for model fit graphically. Each chart (except the last one) plots 200 runs of the model with each point representing a ($y_i$, $f_i$) pair. In other words, a point at say (0.7, 1.2) indicates the parameter value for that run is 70% its base case value, and the *fit* metric produced by that run is 20% greater than $fit_b$. Note that a lower value for fit—which is a measure of error—

means a better fit. For each run, I vary only a single parameter (i.e., the plots for each parameter represent separate run sets), and a value near 1.0 indicates a run very similar to the base case. Visual inspection reveals that the *g* parameter is by far the most sensitive parameter in the IncomeAndCosts rules. This is not surprising since *g* is an exponent in Equation (10). The *a* parameter seems to have less sensitivity than it displayed in the Chapter 4 model. However, in Chapter 4, I varied the parameter over a wide range—from 0 to 0.225—whereas in the plot in Figure 42 the range is only from 0.04 to 0.12 in keeping with the design to test local sensitivities. Also, it is possible that other factors in the model might have muted the influence of this parameter. The last graph in Figure 42 displays the average fit for different mixes of the two rules: LogRegression and IncomeAndCosts. Each point shows the mean value of *fit* for 100 runs divided by $fit_b$, and the error bars display 95% confidence intervals. The red box indicates the base case value. This graph shows that fit is reasonably sensitive to the choice of desired expenditure rules. A mix of 1/3 IncomeAndCosts agents and 2/3 LogRegression agents seems to produce the best fit. Interestingly, the sensitivity is not linear and simulations in which all agents follow a single rule produces a worse fit than situations where agents follow a mix of rules.

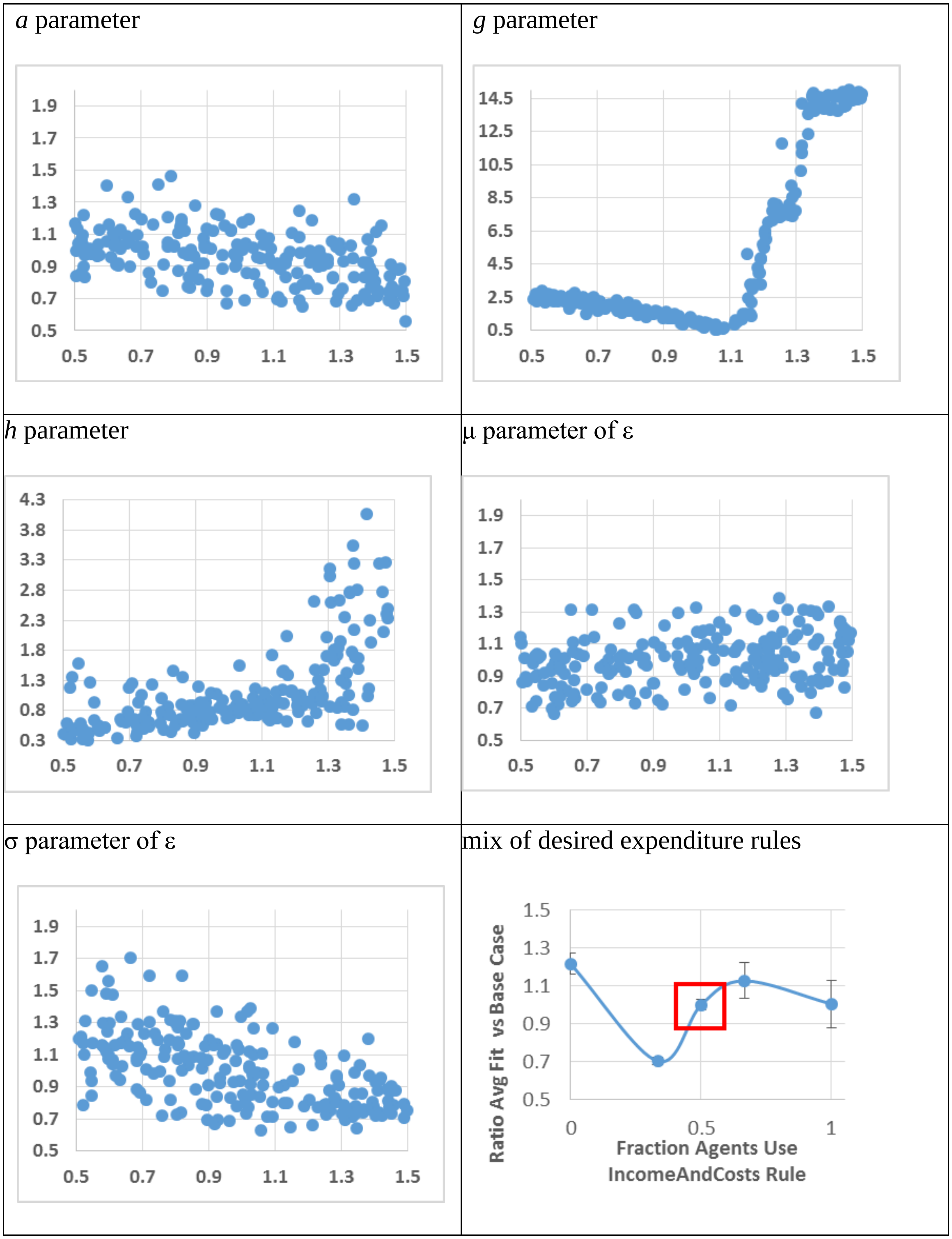



**Figure 42 Sensitivities for desired expenditure rule parameters for the fit metric.**

Figure 43 repeats the graphs using the bubble metric instead of fit. Each chart (except the last one) plots 200 runs of the model with each point representing a ($y_i$, $e_i$) pair. In other words, a point at say (0.7, 1.2) indicates the parameter value for that run is 70% its base case value, and the *extent* metric produced by that run is 20% greater than $extent_b$. Some parameters, such as $a$, $h$, and $\mu$, show clear trends with respect to the bubble. For $a$ and $h$, increasing the parameter value increases the bubble size. For the $a$ parameter, which controls expectations in desired expenditure, this corroborates the counterfactual analysis. The $h$ parameter is a scaling parameter in desired expenditure, and it is intuitive that a larger scaling produces a larger bubble. The $\mu$ and $\sigma$ charts are a bit deceptive since both of those parameters are negative in the base case. Therefore, when $y_i$ is greater than 1, this means the value is more negative than the base case so in fact has been decreased. Thus, the $\mu$ chart implies that increasing $\mu$ (i.e., making it less negative), increases bubble extent. Increasing $\mu$ has the effect of increasing the average desired expenditure since increasing $\mu$ increases both the mean and variance of the $\varepsilon$ heterogeneity factor in desired expenditure. The last graph in Figure 43 displays the average bubble extent for different mixes of the two rules: LogRegression and IncomeAndCosts. Each point shows the mean value of *extent* for 100 runs divided by $extent_b$, and the error bars display 95% confidence intervals. The red box indicates the base case value. Interestingly, the base case 50/50 split of the two rules produces the smallest average bubble, and skewing the rule distribution to either LogRegression or IncomeAndCosts results in a larger bubble.

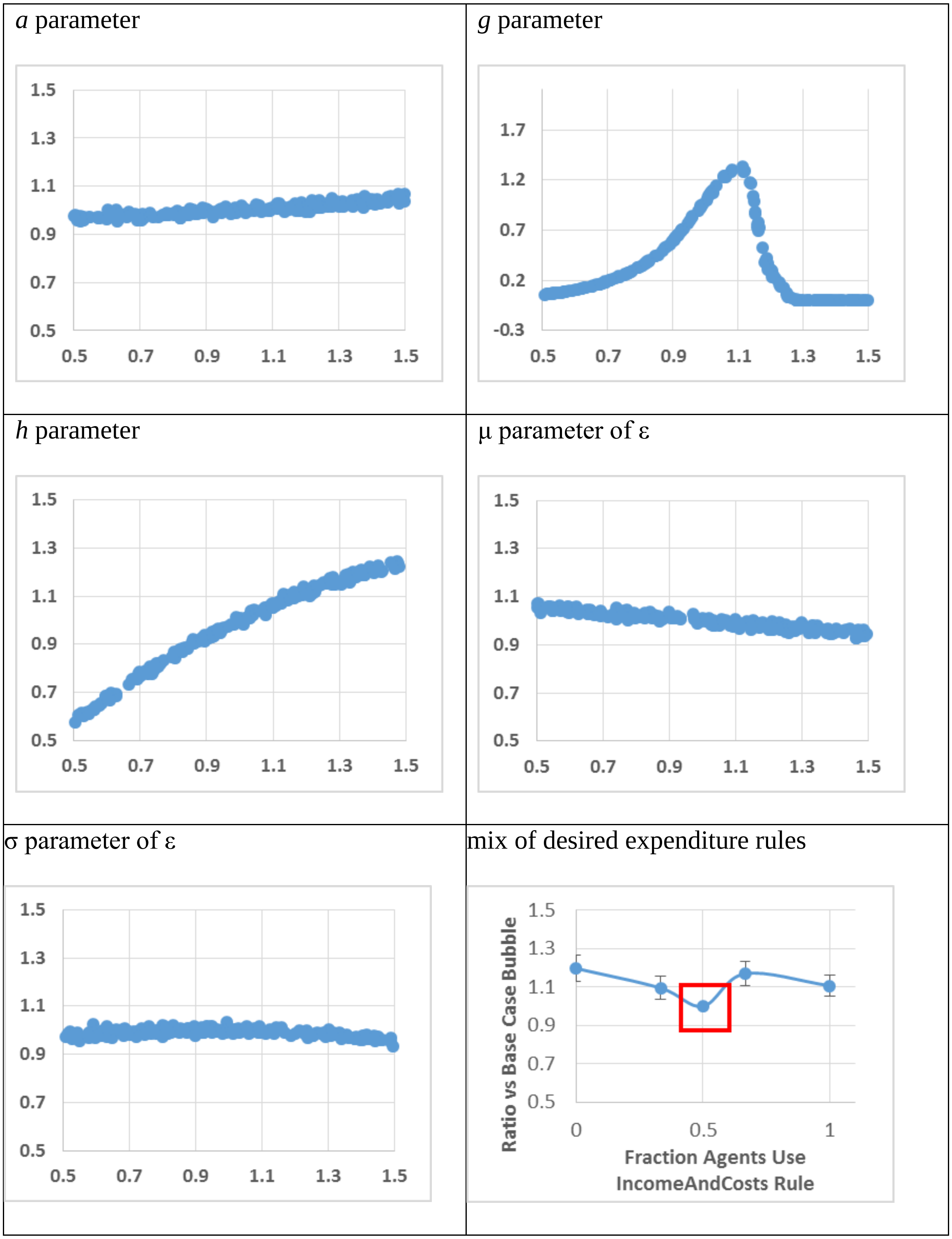



**Figure 43 Sensitivities for desired expenditure rule parameters for the bubble metric.**

Table 5 provides sensitivity values summarizing the graphs in Figure 42 and Figure 43. Columns 3 through 6 report the coefficient of a simple linear regression of $y_i$ on $f_i$ (columns 3 and 4) or $e_i$ (columns 5 and 6). Columns 3 and 5 indicate the sensitivity to increasing $y_i$, and columns 4 and 6 measure the sensitivity to reducing $y_i$. For example, the table shows that a 1% decrease in the *a* parameter produces a 0.32% improvement in fit (note a lower fit is better) and a 0.06% smaller bubble. Not surprisingly, the *g* parameter displays the largest sensitivity, and specifically, increasing *g* produces a much worse fit and much smaller bubble. Of course Figure 42 and Figure 43 shows a bit more nuanced story in which very small increases in *g* actually improve fit and increase the bubble, but moderately small increases make fit much worse and nearly extinguish the bubble. The *h* parameter displays a clear sensitivity trend, especially in bubble extent. Increasing the value of *h* produces a larger bubble and better fit.

**Table 5 Sensitivity values for desired expenditure parameters**

| Param | Base Case Value | Positive Fit Sensitivity | Negative Fit Sensitivity | Pos Bubble Sensitivity | Neg Bubble Sensitivity |
|---|---|---|---|---|---|
| $a$ | 0.08 | -0.32 | -0.11 | 0.10 | 0.06 |
| $g$ | 0.5782 | 37.93 | -3.03 | -2.99 | 1.71 |
| $h$ | 34 | 3.59 | 0.43 | 0.49 | 0.85 |
| $\mu_\varepsilon$ | -0.1646 | 0.05 | 0.21 | -0.11 | -0.10 |
| $\sigma_\varepsilon$ | 0.4335 | -0.41 | -0.50 | -0.09 | 0.05 |

## 5.4. Approved Leverage Module

The other key aspect of the demand side of the model besides desired expenditure is approved leverage. The Chapter 5 model version uses almost the same rule as the Chapter 3 version to determine a prospective buyer's approved leverage. Specifically, the model draws a loan to value (LTV) at origination based on the distribution of LTVs at origination in the historical data for the particular year, dependent on total house price. The LTV data is actually combined LTV (CLTV) which measures the total value of all loans a household uses to buy a house. Then, the model adjusts the LTV and desired expenditure based on some constraints, such as a wealth constraint that ensures households can afford the downpayment and a debt service constraint that ensures the monthly payment of the loan is too large a fraction of the household's income. The Chapter 5 model version has a slight difference: similar to the DTI constraint, banks set a leverage constraint on all loans, and this leverage constraint varies over the course of the simulation. For example, during the bubble this constraint is quite lax (e.g., greater than 0.96 in 2006), whereas prior to the bubble this constraint is stricter (e.g., around 0.9 in 2003).

Because leverage is such an important factor in the counterfactual analysis, it is important to measure the model's sensitivity to leverage. Therefore, I introduce a parameter called $m$ as a maximum leverage parameter that functions similar to the LTV constraint described above and also similarly to the LTV maximum in the counterfactual analyses. The bank's LTV constraint is the minimum of $m$ and the base case constraint applicable in the given year. For example if $m = 0.9$ then no household can receive an approved leverage greater than 0.9 at any time in the simulation. Any approved LTV above 0.9 is automatically reduced to 0.9 and then checked against the wealth constraint. The base case value for *m* is 1.0, and a value for $m \geq 1.0$ has no effect. Therefore, I only consider the sensitivity of *m* in the negative direction.

Figure 44 produces scatter plots for *m* sensitivities both for the fit and bubble metrics. As before, the *x*-axis measures the parameter value relative to the base case value (which equals 1.0 in both cases). For the *fit* graph, the y-axis measures the fit of the run compared to base case $fit_b$ value, and for the extent graph, the *y*-axis measures the bubble extent of the run compared to the base case $extent_b$ value. Bubble extent is highly sensitive to the *m* parameter, corroborating the counterfactual analysis.

*m* parameter - fit | *m* parameter – bubble extent

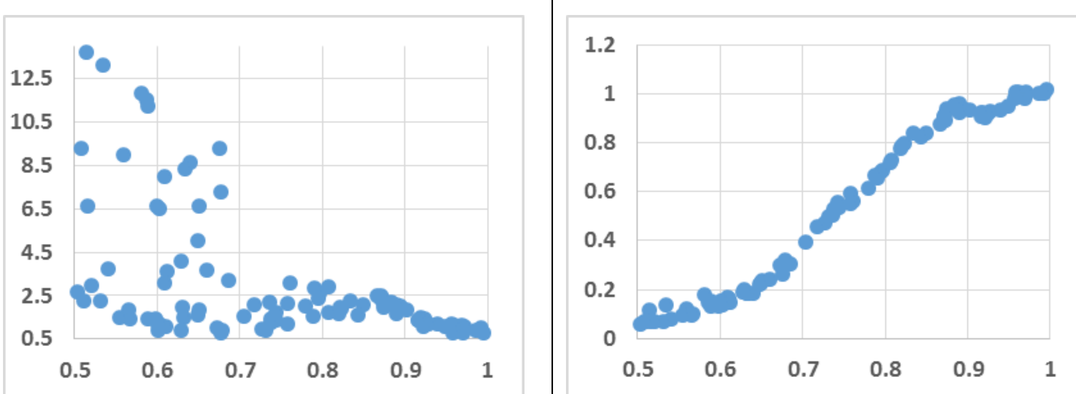



**Figure 44 Sensitivities for approved leverage module parameters for both fit and bubble metrics.**

Table 6 reinforces the visual evidence in Figure 44. Both fit and bubble sensitivities are quite high for the leverage maximum parameter. Since the base case value is 1.0 and any value above 1.0 is non-binding, I only compute the sensitivity of reducing $m$.

**Table 6 Sensitivity values for approved leverage maximums**

| Param | Base Case Value | Positive Fit Sensitivity | Negative Fit Sensitivity | Pos Bubble Sensitivity | Neg Bubble Sensitivity |
|---|---|---|---|---|---|
| ***m*** | 1 | N/A | -10.42 | N/A | 2.35 |

## 5.5. Seller Module

Whereas the desired expenditure rule and approved leverage module influence the demand side of the model, I now consider the supply side—specifically how sellers set their initial list prices and adjust list prices over time. The Chapter 5 version of the model implements a different rule for seller behavior than the Chapter 4 version does. The team estimated the following rule for initial seller list price from MLS data:

$$P = \exp(0.22 + 0.99 * \log(\bar{p}) + 0.22 * \log(s) - 0.01 * \log(DOM) + \varepsilon \qquad (11)$$

Where

- $P$ is list price
- $\bar{p}$ is the average list price of the $n$ closest-quality houses in the past $t$ months. In the base case, $n$ = 8 and $t$ = 6.

- $s$ is the average ratio of sold price to original listing price of houses sold in the most recent month, computed endogenous to the model.
- *DOM* is the average days on market of houses sold in the most recent month, computed endogenous to the model.
- $\varepsilon$ is random noise and is drawn from an empirical distribution of $\varepsilon$ values from the original estimation

In Equation (11), the most important parameters to test for sensitivities are $n$ and $t$ since those parameters were not estimated from the data but whose only justification is that they seem like reasonable numbers. I also wanted to test how the use of this rule compares with the rule in Chapter 3. Recall that with the old seller rule from Chapter 3, sellers compute a "fair market value" of their house as quality * HPI and then markup that value by a randomly factor (sampled from U(1.0, 1.07) in the runs in Chapter 3).

The other aspect of the seller rule determines how sellers markdown their price when a house remains unsold. The Chapter 5 version of the model determines the probability of markdown and the fraction markdown empirically based on months on market and previous price changes. Although this methodology is reasonable, it does not consider the relationship of the sale price to the homeowner's mortgage size or to the price at which the homeowner originally purchased the house. Homeowners might be loss averse either as compared to original purchase price or as compared to current home equity. Note that the model ensures homeowners do not sell a house for a price lower than a homeowner's total wealth (i.e., equity plus liquid wealth minus mortgage size).

I compare the base case markdown rule to two variations. The first variation prevents a homeowner from selling a house at a price lower than its current debt on the house as measured by the outstanding principle on its loan. This variation ensures homeowners do not sell themselves under water (i.e., in which a house's sale price does not fully payoff the home loan). The second variation reduces the likelihood homeowners will sell their house for less than its purchase price. Specifically, the model includes a parameter $z$, which reduces the probability of a price markdown that reduces the list price below the homeowner's purchase price. For example, if a homeowner bought a house for \$200,000 and $z = 0.1$, then any markdown that results in a list price below \$200,000 occurs with probability 10% below the empirical probability. Other markdowns (say a markdown from \$250,000 to \$240,000) are unaffected by $z$. The base case value of $z$ is 0, since it does not make sense to consider negative values of $z$, I consider the sensitivity of the model to values of $z$ from 0 to 1.

Figure 45 displays the sensitivities of the $n$ parameter (which measures the number of similar quality listings polled when setting initial list price), $t$ parameter (which measures how many months back to consider when polling), and new $z$ parameter (which measures loss aversion). The blue scatter plot represents the results of individual runs, and for the discrete variables $n$ and $t$, the green line represents the mean value of the fit for each value of the parameter. Figure 45 shows that model results are not particularly sensitive to the $n$ parameter with values from 4 to 12 producing about the same results.

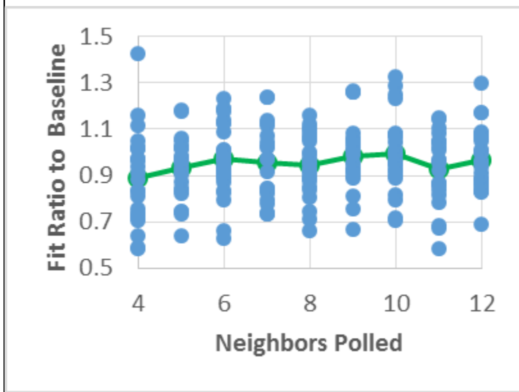
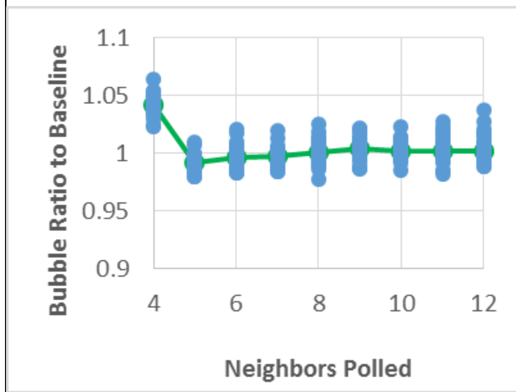
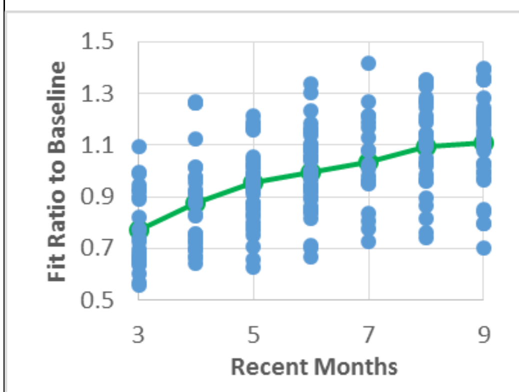
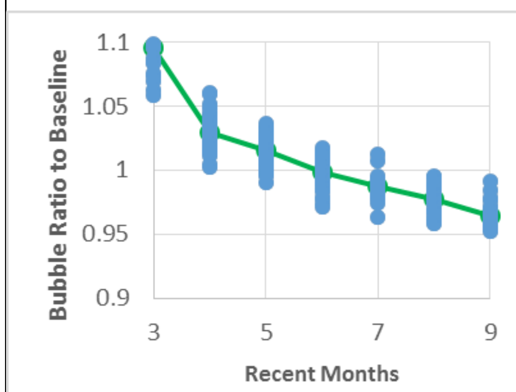
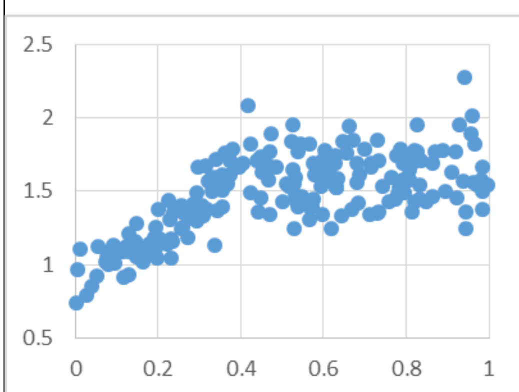
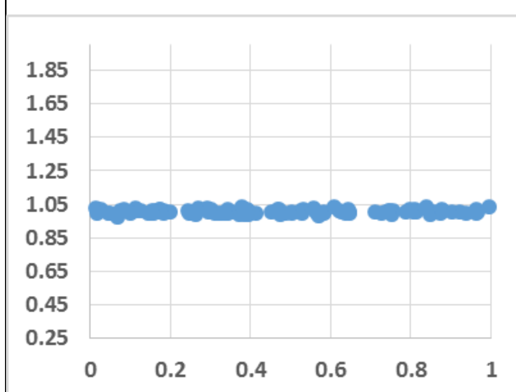
| | |
|---|---|
| *n* parameter - fit   | *n* parameter – bubble   |
| *t* parameter - fit   | *t* parameter – bubble   |
| *z* parameter – fit   | *z* parameter – bubble   |

**Figure 45 Sensitivity analysis for seller parameters**

I did run a two sided t-test comparing each value of $n$ to the base case value of 8 and verified there were cases when I could reject the null hypothesis that $fit_n = fit_b$ (e.g., $n = 4$) at the 95% level. Still, the actual effect on model results of modifying $n$ is slim. The $t$ parameter does seem to have more of an impact with lower values of $t$ showing better fit and a larger bubble, and higher values worse fit and a smaller bubble. Values of $t = 3$ and $t = 4$ produce significantly better fits and higher bubbles than the base case (p-value < 0.01 in both cases), and values of $t = 8$ and $t = 9$ produce significantly worse fits (p-value < 0.01 in both cases), but with about the same bubble extant as the base case. The model does display sensitivity in fit to the loss aversion $z$ parameter, but the bubble metric is practically the same regardless of the value of $z$. This can be explained by the fact that during the bubble period, households almost never sell at a loss. Therefore $z$ does not affect the model during the bubble period. However, other periods such as the early part of the simulation or the crash period produce more muted losses due to loss aversion. Thus, the $z$ parameter affects fit, but not bubble extent.

Figure 46 presents sensitivity results for the seller rule. In both plots, the first column plots 100 runs of the base case; the second column plots the version of the model using the initial list price algorithm described in Chapter 3; and the third columns makes a small modification to seller markdown behavior preventing a household from selling a house for less than the outstanding principle of its mortgage. Columns two and three are independent tests—i.e., the third column uses the Chapter 5 list price algorithm described in Equation (11) and the second column does not include the markdown modification used in the third column). In each case, I execute 100 runs of the model. Figure 46 shows that the fit gets significantly worse and the bubble significantly larger using the simple markup rule (Chapter 3 rule). Thus, although some particular parameters of the seller rule (such as the number of neighbors polled) are unimportant to model output, the model is highly sensitive to the seller module. A two tailed t-test confirms the means of the two distributions are not the same (p-value < 0.0001). The third column which tests a small modification to the seller markdown behavior shows practically no variation from the base case.

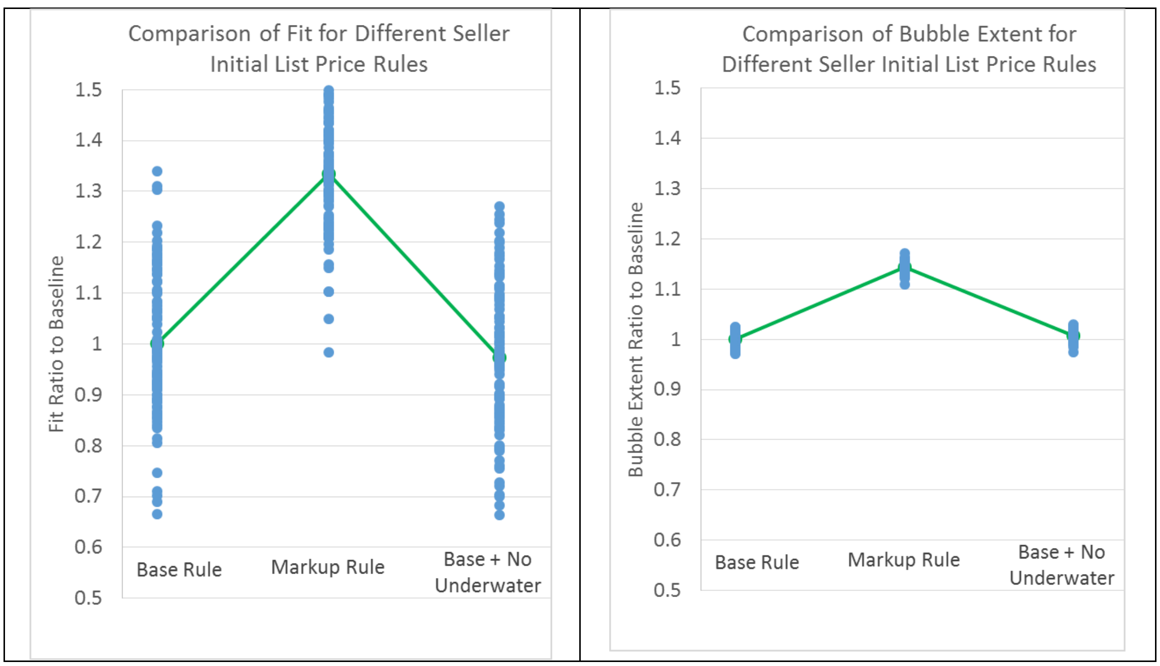



**Figure 46 Comparison of fit for different seller initial list price rules**

## 5.6. Default Module

Defaults are a key aspect of many housing crisis hypotheses because they reduce demand (by excluding foreclosed homeowners from purchasing new houses due to bad credit), reduce the overall quality of houses, and due to their visibility, play a role in changing population expectations. The Chapter 5 model implements a slightly updated version of the rule from Chapter 3. The Chapter 3 model version implements default as a probability based on current loan LTV, and the team calibrated a non-linear rule from LoanPerformance data (see Figure 12 for empirical values). The probability of default, conditional on LTV, remains static throughout the model run, but in reality, expectations likely play a role in strategic default. In other words, homeowners should be less likely to default when prices are appreciating because they expect their LTV to decrease in the future. Similarly, when prices are declining, homeowners expect their LTV to increase over time, increasing propensity to default. The Chapter 5 rule adds this facet. Using LoanPerformance data, the team estimated the following equation

$$P(Default) = \max\{LTV - 0.5, 0\} * (d - j * HPA) \tag{12}$$

The *d* parameter models the increase in marginal likelihood of strategic default as LTV increases[9], and the *j* parameter modulates the effect current market trends have on

[9] In this equation, LTV is measured as a fraction (i.e., with a value of 1 indicating loan = value), not on the percentage scale (i.e., with a value of 100 indicating loan = value) used in this dissertation.

this marginal likelihood. In the base case, $d$ = 0.0087 and $j$ = 0.0235. Figure 47 presents the sensitivity analysis results for these parameters. For both parameters, there appears to be no apparent sensitivity in the local region around the base case model parameter. The sensitivity scores in Table 7 corroborate the observation of low sensitivity.

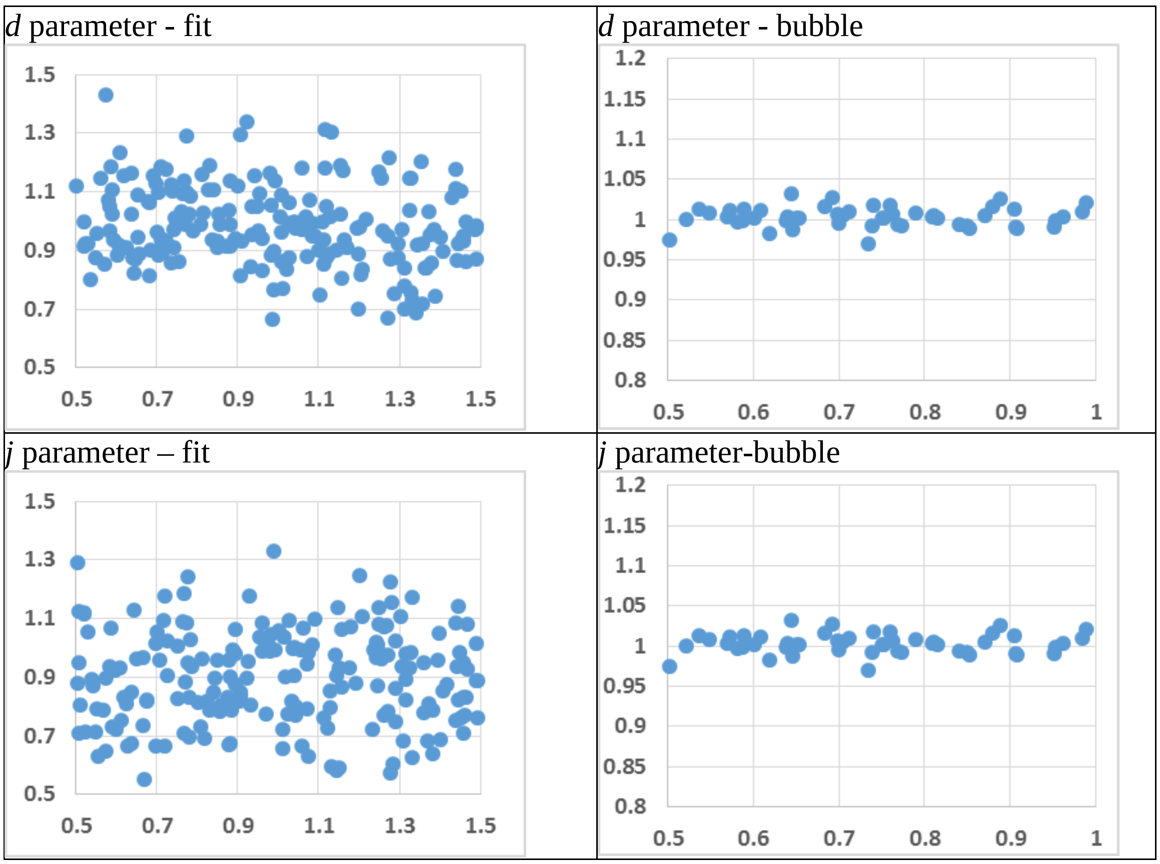



**Figure 47 Sensitivity analysis for default parameters**

**Table 7 Sensitivity values for strategic default parameters**

| Param | Base Case Value | Positive Fit Sensitivity | Negative Fit Sensitivity | Pos Bubble Sensitivity | Neg Bubble Sensitivity |
|---|---|---|---|---|---|
| ***d*** | 0.0087 | -0.10 | -0.02 | -0.007 | 0.004 |
| ***j*** | 0.0325 | -0.008 | 0.15 | 0.003 | 0.004 |

Figure 48 compares the model fit and bubble extent of the base case rule from Chapter 5 (which I call LTV + HPA based rule) to the Chapter 3 rule (which I call LTV based rule). The model fit is slightly better and bubble extent slightly greater for the older LTV-only rule (t-test yields significance with p-value < 0.0001), but the difference is slight. Recall that the LTV-based rule was nonlinear with the probability independently estimated for each LTV bin. In other words *P(Default* | 90 < LTV < 100) was independently estimated from *P*(*Default* | 100 < LTV < 110). This non-linearity might have made the old rule more accurately reflect the data—and since LTVs > 100 occurred mostly during the crash, the binning might have inadvertently picked up the effect of expectations.

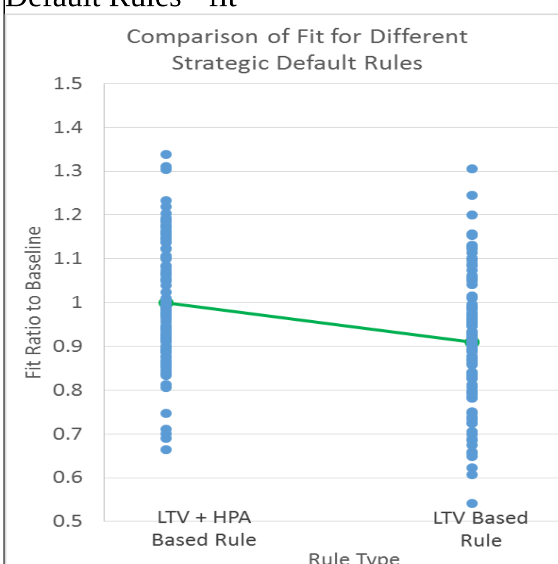
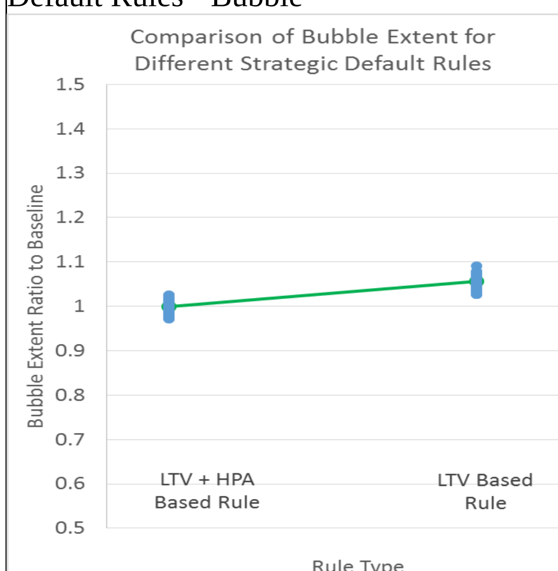
| Default Rules - fit | Default Rules - Bubble |
|---|---|
|   |   |

**Figure 48 Comparison of fit for different strategic default rules**

## 5.7. Refinance Module

Refinance plays significantly into many theories of the crisis (e.g., Khandani et al. 2009 and Gorton 2008). However, in Chapter 3, I found little effect of refinance in the house price model. Chapter 5 keeps essentially the same rule as Chapter 3 but with one extension. Recall the Chapter 3 rule—described in Equation (5)—models cash out refinance probability as linear in current loan LTV. The equation has two parameters: $k$ and $l$, and I investigate the sensitivity of these parameters. The $k$ parameter is a linear parameter that increases the marginal probability of cash out refinance as LTV decreases (i.e., home equity increases). The $l$ parameter is a threshold parameter that determines the point at which households consider cash out refinance. In the base case $k = 0.009$, and $l = 0.85$ (synonymous with LTV = 85). Recall from Equation (5), the linear scaling is actually ${}^{k}/_{l}$, meaning a decrease in LTV by one point increases the probability of refinance by about 1/100$^{th}$ of a percent. Households do consider refinance every month so there are many opportunities to refinance. There is one addition to this rule for the Chapter 5 version. Households that have fallen behind on payments (i.e., are one month delinquent on their loan) due to cash flow issues also seek to cash out refinance. This addition captures the insight from Gorton (2008) and others that the end of the teaser period on an ARM loan can trigger refinance decisions that often lead to equity extraction. When the teaser period ends, monthly payments shoot up causing households to become delinquent. Households might try to refinance into a new ARM loan with a new teaser period, but in the process extract equity, increasing their leverage and susceptibility to becoming underwater on their loan.

Figure 49 displays the run results from varying the *k* and *l* parameters, revealing very little model sensitivity to these parameters. Table 8 corroborates this observation with low sensitivity numbers for both parameters. Similar to the counterfactual analysis in Chapter 4, model results do not seem to be that dependent on cash out refinance levels.

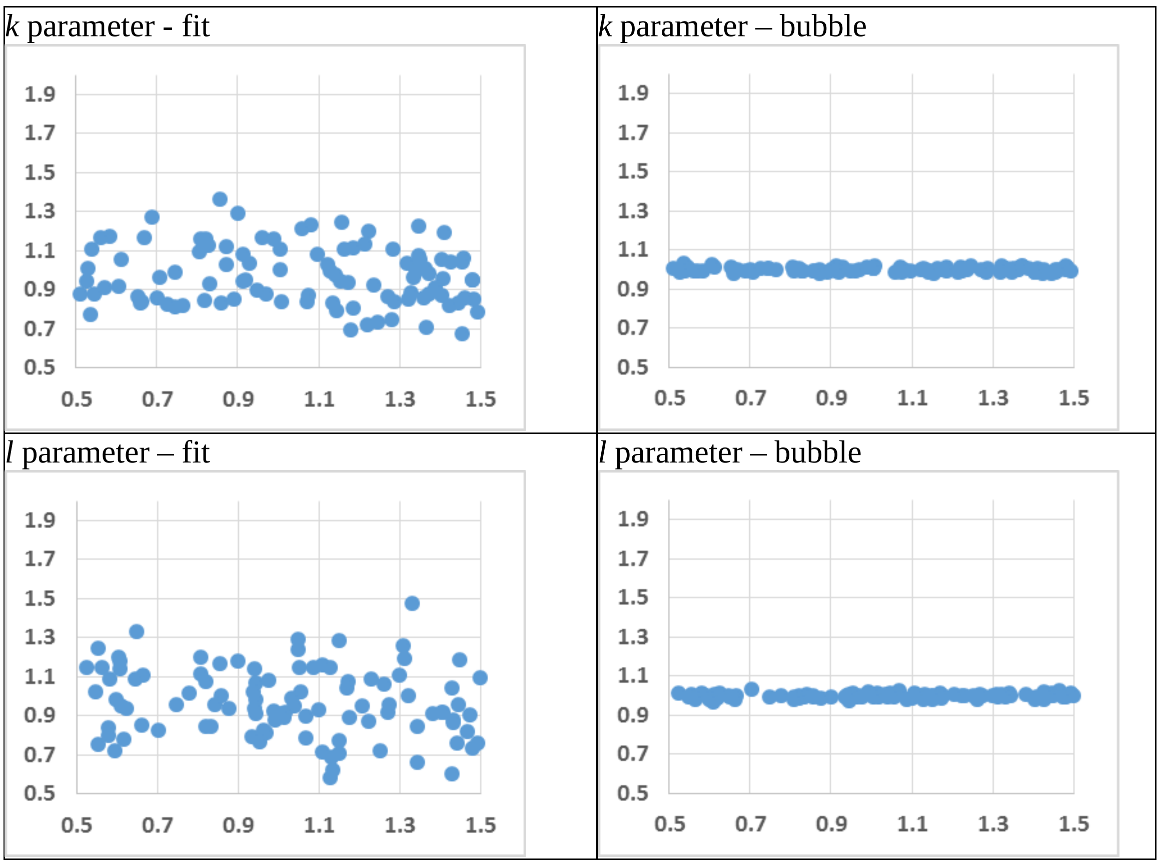



**Figure 49 Sensitivity analysis for cash out refinance parameters**

Table 8 Sensitivity values for cash out refinance parameters

| Param | Base Case Value | Positive Fit Sensitivity | Negative Fit Sensitivity | Pos Bubble Sensitivity | Neg Bubble Sensitivity |
|---|---|---|---|---|---|
| ***k*** | 0.009 | -0.19 | 0.21 | -0.003 | -0.01 |
| ***l*** | 0.85 | -0.14 | -0.15 | 0.003 | 0.004 |

Figure 50 compares the model fit of the base case rule from Chapter 5 (which I call LTV + 1DQ rule) to the Chapter 3 rule (which I call LTV rule). The only difference is that households might cash out refinance when they fall behind on their payments (if they have enough equity accrued to recoup the refinance cost of $5000). The model fit is slightly better for the old rule without the addition of the one month delinquency motivation (t-test yields significance with p-value < 0.0001), but the difference is slight. Similarly, the bubble extent is slightly greater for the old rule (t-test yields significance with p-value < 0.0001), but again the difference is slight. As previously, all points in both graphs are scaled by the average base case fit and bubble extent respectively.

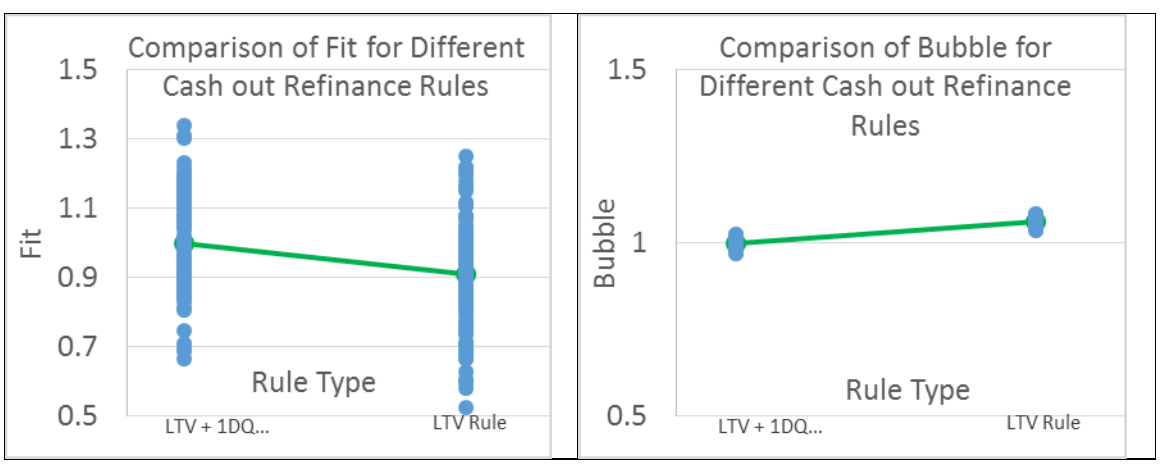



Figure 50 Comparison of fit and bubble for different cash out refinance rules

## 5.8. Combining Leverage and Expectations

Next, I considered the interaction of leverage maximums and expectations. These two aspects of the model figured heavily in the counterfactual analysis in Chapter 4, and the model was sensitive to both parameters in this chapter's analysis. However, targeting either one with policy has complications. In the case of expectations, it is not clear exactly what policy lever would temper households' use of expectations. In the case of leverage, a draconian leverage maximum extinguishes the bubble, but likely only a modest leverage maximum could be implemented (or more likely, some incentives to limit leverage). The question is then whether there is a sweet spot in which somewhat lower leverage and somewhat less reliance on expectations avert the housing crisis.

Figure 51 probes this question by varying the *a* parameter in desired expenditure (which controls expectations) and the *m* parameter that sets a maximum leverage. The top chart displays the raw HPI maximum (bubble extent metric). The color in the figure represents the value of the bubble extent, with dark blue corresponding to the base case 1.7 value. Here, we see that *m* parameter has a much greater influence than the *a* parameter in limiting the bubble extent, and there appears only a slight interaction. For example, color bands seem to be reasonably horizontal, which corresponds to changes in *m*. On the other hand, the lower chart, which shows the simulation month at which the model reaches its HPI maximum, indicates the *a* parameter has a greater influence. The maximum HPI month corresponds to the market peak and onset time of the crash. The light blue in the top right indicates a value around month 123, which is the base case value (corresponding to early 2007, a bit after the actual peak in historical data). Decreasing either *a* or *m* pushes this peak outward, reaching a maximum value of 155. 155 is the last month of the simulation, and this value indicates the run contains no crash. This suggests a modest change in both *a* or *m* might avert the crash (or at least delay it) even if only changing *m* has a significant effect on the bubble size.

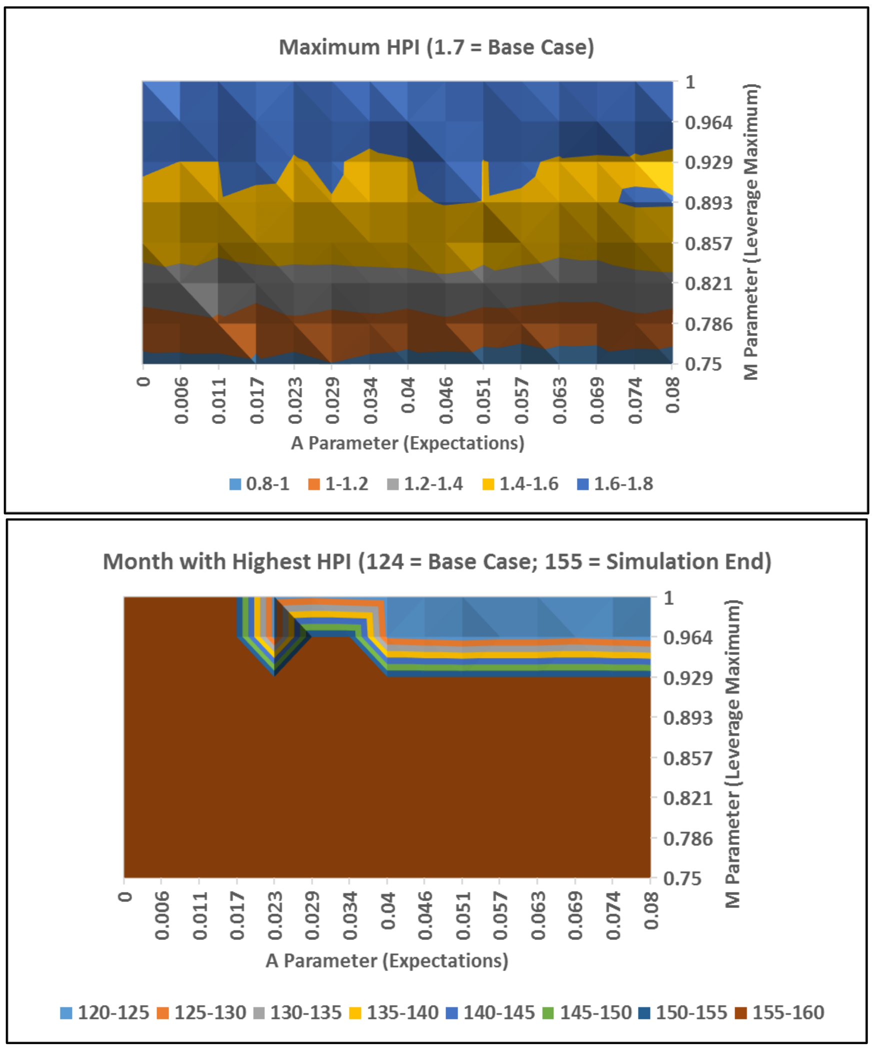



**Figure 51 Combined influence of leverage and expectations on bubble height and shape.**

## 5.9. Sensitivity Analysis Conclusion

The sensitivity analyses in this chapter investigated some of the major rule decisions and parameter values. In general, the model was not that sensitive to most of the rules and parameters—with a few exceptions such as the choice of initial list price, approved leverage maximum, and some of the parameters in the desired expenditure rule. I only tested small variations in parameters and rules because the purpose of this analysis is to understand how much model results depend on using exactly the right parameters and rules. As discussed earlier, the parameter estimations often use data that is not exactly analogous to the behavioral rules in the model. For example, the team calibrated desired expenditure using actual expenditures and strategic default using all defaults. Therefore, the parameter estimates are likely somewhat inaccurate, but not likely to be terribly wrong. Thus the sensitivity analysis considered whether model results would change drastically if these small errors were corrected.

Similarly, there is no perfect science for determining the exact behavioral rules agents follow, and most likely, heterogeneity in the real world is beyond the power of computer models to capture. However, there are empirical and behavioral studies that provide some basis for setting rules. Therefore, similar to the parametric estimates, the model rules are likely approximately correct, but contain some error. For example, we know that the prevalence of default is correlated with low home equity (e.g., see Archer and Smith 2010), but we do not know exactly how much expectations of future price movements, which alter home equity levels, influence the strategic default calculus. Therefore, I tested the sensitivity of alternative default rules—one with and one without these expectations included. In that particular case, the model sensitivity was low, suggesting that according to the model the distinction is not important. On the other hand, I compared two seller list price rules, both of which consider current market conditions. One rule samples similar houses, whereas the other uses the house price index directly, and I found that the model was quite sensitive to this choice. These results should target future research toward studies that help pinpoint the correct behavioral rules and parameters for seller initial list price setting. More broadly, analyses such as the one conducted in this chapter are an essential precondition to understanding model behavior and interpreting model results.

# 6. EXTENDING THE MODEL: MORTGAGE BACKED SECURITIES

One area in which the base housing market model is lacking is the banking sector. The housing market is inextricably linked to the larger financial system, and whereas this dissertation has focused on proximate causes of the housing crisis, such as leverage, interest rates, expectations, and lending standards, the underlying causes of some of these originate in the financial sector. For example, the incentive to weaken lending standards or extend credit requiring low downpayments originates in the financial sector. Similarly, the abrupt changes in lending practices that sparked the housing crash originated in the financial sector as well. This chapter describes an agent-based model that combines a housing market and a simple financial market. The model specifically investigates the role residential mortgage-backed securities (RMBS) played in causing the housing crisis. The model was constructed on an entirely separate code base as the housing market models discussed in Chapters 3, 4, and 5. Importantly, it does not use the data that the base housing market uses[10], but it does employ a qualitatively similar housing market as the base housing market model. In the future, some of the model structure from this model could be integrated into housing market model's code base to improve handling of banking sector. The remainder of this chapter describes the RMBS-housing model and analyzes it.

[10] Unfortunately, there is much less data available on mortgage derivatives.

## 6.1. Model Background and Motivation

Although many elements of the crisis are understood—the bursting of the housing bubble, a liquidity shortfall, a run on certain types of securities, etc.—both the precise causes of the crisis and similarly what could have been done to prevent the crisis are matters of considerable debate. Without using simulation models, economists have provided a number of hypotheses on the crisis's origin. One hypothesis blames the practice of banks securitizing mortgage loans and selling these securities to investors. This practice lowered banks' incentives to price loan risk because banks no longer bore most of this risk. Furthermore, investors who bought the securities were too far removed from the loan origination to price the risk (see e.g., Ashcraft and Schuman 2008 who list this and other incentive problems with subprime origination, such as the principal agent problem between investors and asset managers). This hypothesis might be referred to as the "originate to distribute" hypothesis because it centers on the practice of originating loans to sell them as securities (i.e., distribute). A competing hypothesis argues that originate to distribute works in sectors other than subprime mortgages, and hence, it is the subprime mortgages that are the culprit, not the practice of securitization. Specifically, subprime loans were given to borrowers on terms that were too onerous for borrowers in the absence of house price appreciation and refinance. When house prices stopped appreciating, people started defaulting. When it was revealed to investors through futures indices that it was common knowledge that everyone thought subprime loans were poor investments, a run on securities that might be backed by subprime loans ensued (Gorton 2008). Finally, a third hypothesis blames the crisis on lack of regulation of the shadowing banking sector. Specifically, non-bank financial entities that trade in securities and commercial paper were not backed by government guarantees, such as those provided by the FDIC to depositors, or a lender of last resort, such as the Fed discount window. Proponents of this hypothesis see the financial crisis as similar to banking panics that occurred before the institution of federal deposit insurance (Pozsar et al. 2010). A variation of this hypothesis blames financial institution's engaging in regulatory arbitrage to get around capital requirements. They did this by selling loans to off balance sheet entities, even though these entities were in the end backstopped by the bank. The off balance sheet entities could take on much higher leverage than the bank would have been allowed based on regulations, even though these entities implicitly affected the financial viability of banks.

In this chapter, I describe an agent-based model aimed at testing these hypotheses. Although the model needs more work before it can provide compelling evidence to any side of debate, it already shows promise in uncovering the nature of the dynamics that caused the financial crisis. This model, which I describe more fully later in this chapter, models both the residential mortgage market and contains a simple model of the mortgage backed securities market. I show that the model can reproduce some empirical facts of the financial crisis, such as a housing bubble, defaults on subprime loans in the absence of house price appreciation, and increased loan origination when banks can create securities and sell these securities to investors.

## 6.2. Related Literature

By now, there has been an extensive literature describing the origins of the 2007-2008 financial crisis. Notably, Gorton (2008) provides a thorough description of how mortgages get packaged and then sliced up into asset backed securities (ABSes), how ABSes get further packaged and sliced into collateralized debt obligations (CDOs), and the types of entities involved in the chain from mortgage origination to investment in CDOs. He also provides a hypothesis, described in the previous section, of the cause of the financial crisis as being specific to the nature of subprime loans and the sudden revelation of negative investor sentiment about these products to all investors. Pozsar et al. (2010) provide a thorough description of the shadow banking system and its role in the crisis. Khandani et al. (2009) describe how low interest rates, rising home prices, and easy money led people to continually build up leverage through cash-out refinancing—which they term the "ratchet effect." The ratchet effect led to systemic risk as many homeowners became highly leveraged. When interested rates increased, causing a drop in home prices, the only mechanism available to households to deleverage was default. Archer and Smith (2010) analyze defaults and give the two leading causes as a high (greater than one) loan to value ratio and a high ratio of monthly mortgage payment to income. They also show that during times of house price appreciation, lenders typically relax standards on lending, increasing the size of housing bubbles and the negative effects of the bursting of these bubbles.

There is also a large literature base in economics on the effects, and to a lesser extent, the causes of financial crises. Bernanke et al. (1996) famously describe the credit channel effect through which disruptions in the financial sector can affect the real economy by restricting credit to firms that most need it. The model I present currently does not focus on the real economy so I do not build off of Bernanke et al.'s idea, but it is a rich avenue for future exploration. Geanakoplos (2010) describes the "leverage cycle," in which the most optimistic buyers of an asset drive prices up during boom times. These traders become heavily leveraged in order to buy the asset, and as long as the asset's price is rising, these traders will gain more wealth and further drive the asset price up. Once the asset price goes too high and optimism wanes, the price starts falling and the optimistic traders lose wealth. The asset falls more and more into the hands of pessimistic traders further driving down its price. The cycle, which Geanakoplos terms the leverage cycle, exacerbates price cycles in assets. The leverage cycle mechanism in which asset booms become inherently unstable due to excess leverage is similar to the theme in Minsky (1986). Finally, there is also a large literature on financial crises. See especially Reinhart and Rogoff's (2009) panoramic study of financial crises covering 66 countries and dating back to the $14^{th}$ century for some countries.

In building an agent-based model to capture many of these insights, there were a number of sources from which I could draw. Delli Gatti et al. (2011) provide one of the best published macroeconomic models. The authors model the interactions between firms, banks, and individuals and are able to produce business cycles, typified by sustainable growth, followed by leveraged growth, followed by bankruptcies, and finally a consolidation of positions. There are many agent-based models of financial markets, such as Lux (1998), LeBaron (2001), and Alfarano and Lux (2007) to name a few. These models typically contain agents that price a risky security using some heuristic procedure, such as reinforcement or imitative learning. Additionally, there have been a few agent-based models of the financial crisis already published. For example, Markose et al. (2010) presented a paper using an agent-based model to shed light on the systemic risk caused by credit default swaps (CDSes).

## 6.3. Model Logic

In this section, I describe the algorithms that compose the financial crisis model I built for this chapter. Because I was most interested in investigating how the crisis was triggered, I left out elements of the real economy that would be necessary to understand the crisis's impact. Therefore, the only agents in the model are households, investors, a central bank, and financial institutions[11]. The model also contains other objects, such as houses, loans, residential mortgage backed securities (RMBSes), and RMBS shares. I stepped the model using a one month timestep in which each timestep followed the basic process enumerated below:

1. Households activate sequentially in random order. A household receives income, and performs one of more of the following behavior: pays mortgage or rent, defaults, lists its house for sale, buys a new house, and refinances.
2. Next, financial institutions package new loans into RMBSes.

[11] Financial institutions are essentially banks, but because I rolled up a number of functions such as origination and loan warehousing into one entity, I was really modeling a financial holding company rather than a bank

3. Investors purchase shares in these RMBSes. Investors track the profitability of RMBS shares versus shares in a riskless asset, and place share bids based on this valuation.
4. Accounting is done for the turn. Financial institutions collect money from loans. They pay out to investors holding RMBS shares (described in more detail below) and determine how much cash they have for the next time step to lend.
5. The central bank updates its rate, and the financial institutions use this rate to update their fixed rate loan rate, ARM period one rate, and ARM period two rate for the next timestep.

Figure 52 describes the basic flow of one time step for a household. On the previous time step, the household might have decided it should look for a house (for example, its house sold last timestep or its lease is now up). If the household is trying to buy a house, the household randomly samples some number of houses for sale (in the nominal parameterization I used, this number was ten) and sorts them from highest to lowest quality. The quality of each house is assigned from a Pareto distribution at the beginning of the simulation. Price is highly correlated with quality, and therefore in general, a household tries first to purchase the most expensive house in its random sample. A household applies for a mortgage to some number of financial institutions (two in the nominal case) for the first house on its list. If the household's loan application is approved by one or both institutions, the household chooses the loan with the best terms—always preferring fixed rate over ARM loans. If no financial institution approved a loan for the household, the household proceeds down its list to the next house. If a house was not bought by the end of this list, the household signs a new rental lease.

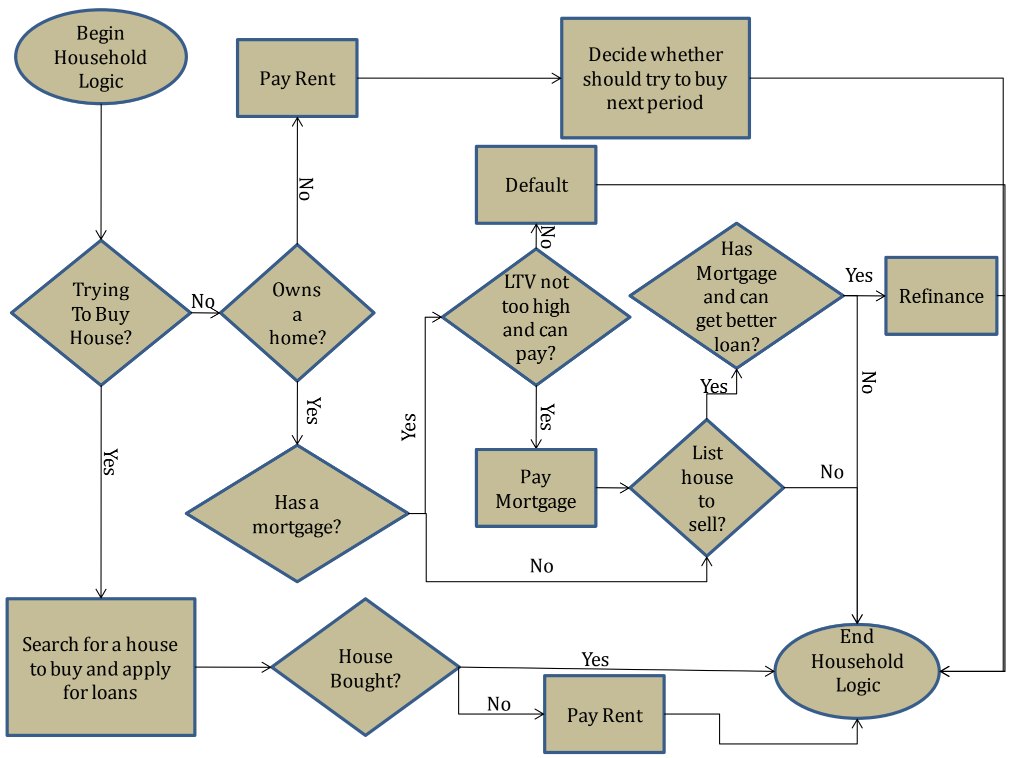



**Figure 52 Model Logic for Households**

If the household currently owns a home (middle diamond in the second column of Figure 52), the household decides whether it can make its monthly payment. The household skips a payment if the loan to value ratio (value is determined as the house's quality times the house price index) of its mortgage is above some threshold (1.2 nominally), or if the household's income plus savings is less than the monthly payment, or the monthly payment is significantly higher than the household's income (1.5 times income in the nominal case). Note that "income" actually represents income minus all non-mortgage related expenditures. In fact, the model variable is called “incomeForHouse.” The household default decision follows from Archer and Smith (2010) who give the two main causes of default as high loan to value ratio and high payment to income ratio. If a household skips a payment, it stops paying its mortgage forever, but does not get kicked out of its house for a number of months (24 months in the nominal case). The quality of the house drops significantly by this default (cut in half nominally), and ownership reverts to the lending institution once the household is kicked out of its house.

If the household does not decide to default, it pays its mortgage. The household has the option to list its house for sale. The list price the household chooses equals the house’s quality times the current house price index times some markup (1.05 in the nominal case). Sellers slowly markdown the price of listed houses as time passes without a sale. When the house is sold, the household tries to buy a house next period (sets trying to buy to true).

If the household does not decide to list its house for sale, the household might try to refinance. The household tries to refinance if the household believes it can get a significantly lower interest rate or its house has appreciated in value significantly, such that the household wants to cash out this increase.

The loan approval process for refinancing is similar to the one for buying a house and graphically displayed in Figure 53. A financial institution begins by determining the value of the house, which will be the loan’s collateral. If the borrower needs a loan to finance a new home purchase, lenders use the purchase price as the home’s value. If the loan application is for refinancing, the home value is appraised to be the house's quality times the house price index. The model computes the house price index similar to the Case-Shiller index (CoreLogic 2016) and is based on the price difference between sequential purchases of the same house. A financial institution only approves fixed rate loans for households who make a 20% down payment and whose income after non house expenses (that is, income for house payments) is reasonably more than the mortgage's monthly payment (10% more nominally). If a household does not meet these criteria, the financial institution considers an ARM loan, which requires no down payment. ARMs are structured as 2/28 mortgages with the first period rate being about 1% less than the fixed rate mortgage rate, and the second period rate being pegged to about 3% more than the current fixed rate mortgage rate, updated every six months. The current fixed rate mortgage rate is of course updated every month based on movements in the central bank's rate. A financial institution approves a household for an ARM loan if the household can make payments on the initial fixed rate (and has a 10% income cushion). Note that there will be many households who meet the ARM criteria who will not be able to make payments during the adjustable period, triggering a refinance attempt similar to the narrative in Gorton (2008). Of course, if home values have depreciated enough or interest rates increased enough, the household will not be able to refinance and will have to default.

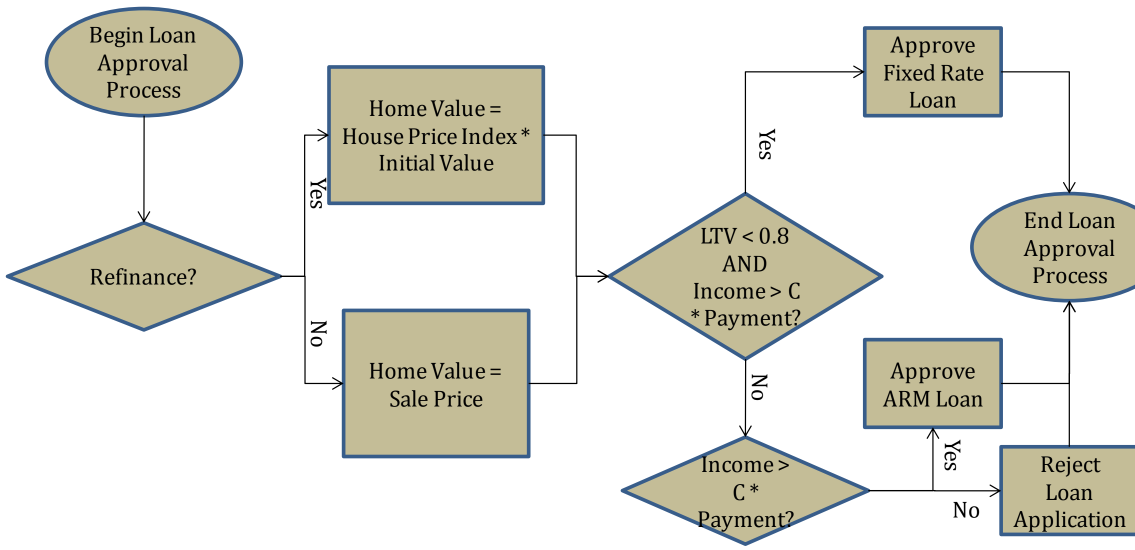



**Figure 53 Loan approval process.**

After the model processes all the households for a timestep, financial institutions take new loans and package them into RMBSes[12]. Figure 54 shows the structure of an RMBS based on the parameterization I used in my analyses (e.g., 80/20 split of senior to junior tranche, etc.). All loans in an RMBS loan pool are new loans on which no payments have been made, and all are owned by the same financial institution. Each RMBS contains only two tranches, a senior tranche and a junior tranche. Each tranche is then divided into a number of shares. The shares represent claims on payment from the underlying mortgages. All shares in a particular tranche have the same priority of payment, but all shares in the senior tranche have priority over the junior tranche. Specifically, if up to 20% of the mortgages default, shares in the senior tranches are

[12] The model abstracts away lots of detail of how mortgage backed securities end up in investor portfolios. Not only do I skip some steps, such as loan warehousing, RMBS warehousing, CDO creation (and possibly CDO$^2$ and further creation), wholesale funding of security purchase, etc. , I also made the RMBSes themselves very simple. I believe this abstraction makes the coding challenge tractable while keeping the essential features of mortgage backed securitization.

unaffected and still receive principal and interest payments. However, the value of junior tranche shares reduces as these shares absorb losses from defaults. Note that to make up for the increased risk, junior tranche shares are paid a higher interest rate than senior tranche shares. In this model, the financial institution keeps all junior tranche shares and sells senior tranche shares to investors. The financial institution also builds in a rate spread of 0.0075% of the value of the loans (that is, not all the interest payments on loans are given to owners of RMBS shares). This spread is used to make up for defaults and paid out to shares if interest payments are not paid on loans, but kept by the financial institution as profit if loans are paid on time.

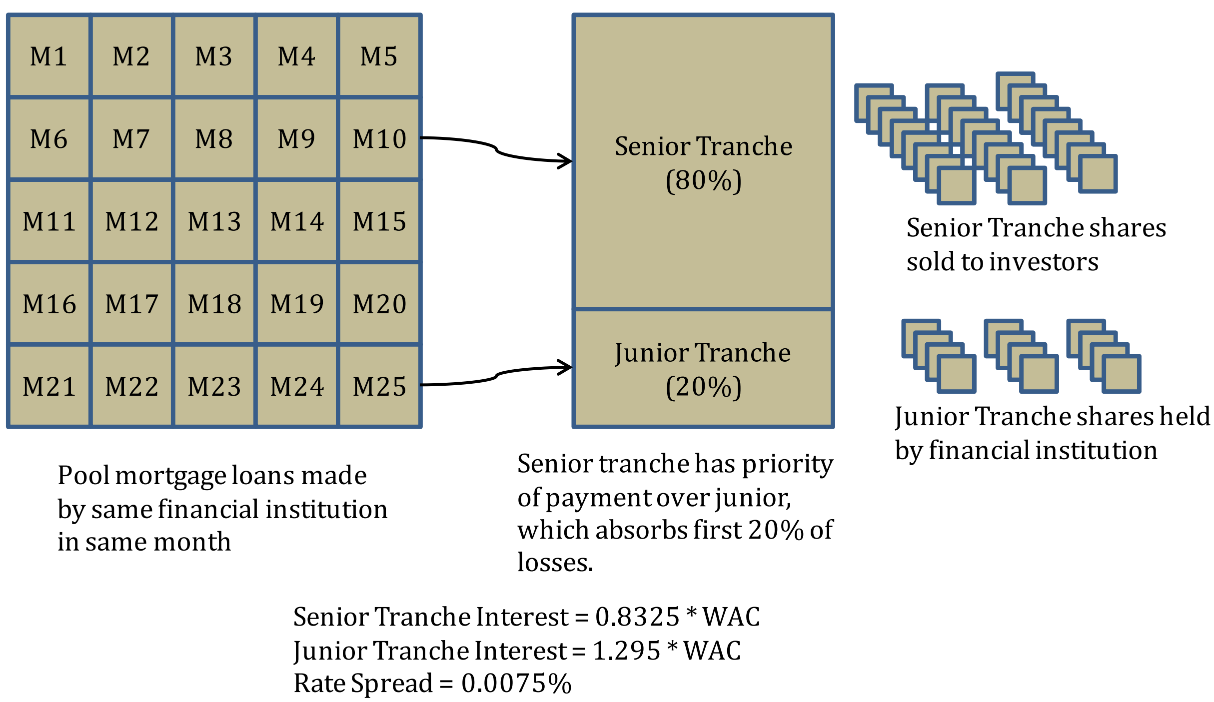



**Figure 54 RMBS Structure**

Next, financial institutions attempt to sell senior tranche shares to investors. Investors have the option of buying tranche shares or a riskless asset whose one period return is equal to about 8 basis points less than the Central bank's rate (the equivalent of 100 basis points less annually). Investors keep track of the profitability of both types of assets each month. Specifically, the realized rate of return on RMBS shares for an investor is:

$$\frac{\text{Interest and Principal Payments} - \text{Reduction in Underlying RMBS Principal}}{\text{Last Month's RMBS Principal}} \quad (13)$$

Principal payments cancel out since they affect both sides of the minus sign in the numerator. Therefore, gross profits each month on RMBS shares equal interest payments minus principal lost to defaults. Gross profits are divided by the total amount of principal invested to determine a rate of return. Each investor has a memory length (from 4 to 15 months distributed uniformly in the nominal case) over which the investor computes an average realized rate of return for RMBS shares. Each investor also keeps track of the average riskless return rate in the same manner. An investor values \$1 of a RMBS share's principal at the following value:

$$\left({}^{1\,+\,\text{Realized RMBS Return Rate}}\!\Big/_{1\,+\,\text{Riskless Return Rate}}\right)^{\text{Memory Length}} \quad (14)$$

Equation (13) suggests that, in times of rising house prices and low interest rates, RMBS shares will be profitable since they return a higher interest rate than the riskless asset and do not suffer many defaults. However, in times of high default, the return on RMBS share investment drops precipitously. Equation (14) suggests that during housing downturns investors will value RMBS shares much less than during housing booms.

The financial market for RMBS shares is quite basic in this model. Investors bid on shares made available by financial institutions based on investors' valuations of RMBS shares. Financial institutions sell shares at the bid prices, selling first to investors who bid the most. Investors who buy shares hold them until they mature, and unsold senior tranche shares are kept by the financial institution and not put up for sale on subsequent timesteps. Investors buy as many shares as they have money to buy and are available (with priority of purchase being determined by bid). The main influence the RMBS market has on the model is quickly freeing up assets of financial institutions to be used to make more loans. In future versions of the model, the RMBS market will drive financial institution lending standards. As demand increases for RMBS shares, financial institutions will be more willing to make loans and might need to approve loans to less qualified applicants to meet demand for RMBS shares.

After the RMBS market completes, financial institutions iterate through the mortgages they service and collect principal and interest payments. These payments are paid out to RMBS shareholders. Next, financial institutions calculate how much cash they can use for loans next time step. First, a financial institution determines its total number of assets, which equals its cash plus its unpacked loans (i.e., those not packaged in an

RMBS) plus its owned RMBS shares plus the houses it owns through defaults. A financial institution is required to keep cash reserves equal to a certain percentage of its risky assets (loans, houses, and RMBS shares). Any cash owned above this requirement is available for loans next time step.

Finally, at the end of the time step, the central bank sets its interest rate to a new rate. The model can do this either via a random walk or update the rate based on an input file. For the model runs analyzed in the next section, I used an input file corresponding to the United States Fed Funds Rate from January 1980 through October 2010. Banks then set their rates based on this rate plus some markup (e.g., 2% plus some small noise value for fixed rate loans).

### 6.4. Preliminary Model Results

I ran the model with 10,000 households, 9,000 houses (note that renters do not actually occupy a house), 10 financial companies, and 1,000 investors. I set house quality using a Pareto distributed with a minimum value of $175,000 and a Pareto exponent of 2.0. Household income and wealth were also both Pareto distributed. For income (really income – non housing consumption), I used a Pareto distribution with a minimum value of $1,000 and a Pareto exponent was 1.5 (note that households making less than this value were considered not part of the housing market). The wealth distribution was parameterized with a minimum value of $18,000 and Pareto exponent of 0.85. These distributions are meant to match stylized facts of housing price, income, and wealth distribution. When the model becomes more mature, I would like to match these more precisely to real data.

The first stylized fact about the crisis I wanted to replicate is the housing bubble. Specifically, I would like to see if the model produces a large spike in housing prices as the central bank rate nears zero; similarly, the house prices should drop sharply when the interest rate increases. Figure 55 graphs the interest rate (fed rate and average financial institution rate for fixed rate loans) in the top panel, and the house price index in the bottom panel. Recall that the central bank rate was based on the United States Fed Funds Rate from January 1980 to October 2010. Also, recall that the house price index is computed, similar to the Case-Shiller index, using the change in sale price in subsequent sales of the same house. As can be seen in Figure 55, house prices do in fact spike as the interest rate declines. Over a 4 year period (roughly timestep 274, corresponding to mid-2002, to 313, corresponding to early 2006), the house price index increases from around 1.0 to over 2.0. In actuality, a similarly large increase occurred in the Case-Shiller index, but the increase started in 1997 (notice that the model run produces an increase around that time as well, but then this mini bubble bursts before the larger bubble occurs). Once interest rates start increasing, the index decreases about 25 to 30%, similar to how the actual Case-Shiller index behaved.

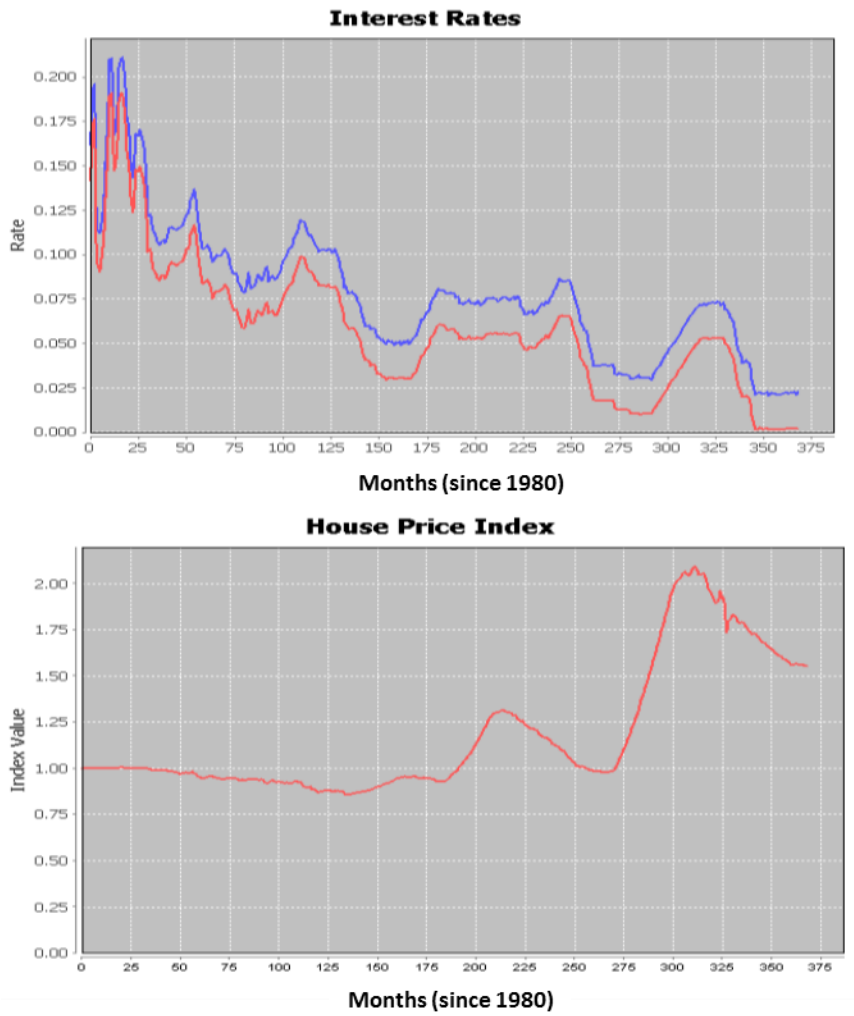



**Figure 55 Home price index as affected by interest rates (red line is the central bank rate and blue line is the average fixed loan rate by all financial institutions)**

Next, I was interested to see how investors valued RMBS shares. Figure 56 plots the riskless asset interest rate (blue line) versus the investor realized RMBS return rate (red line), both smoothed over several months and both reporting annualized return rates. The green line measures the difference between the two lines. Recall that the riskless asset return rate is pegged to 100 basis points below the central bank rate on an annualized basis and declines with the central bank rate for most of the simulation. The

RMBS share return rate is correlated with both the central bank rate (because the central bank rate is ultimately correlated with mortgage rates) and the frequency of default of the underlying mortgages. For much of the simulation, the RMBS shares perform better than the riskless asset until the housing bubble pops near the end of the simulation, and RMBS shares provide a negative rate of return. Note that RMBSes package both prime and subprime loans in the same RMBS, better insulating senior tranche holders from subprime defaults than was the case during the actual crisis. A future version of the model will create RMBSes solely from subprime loans to understand how this practice affected the RMBS market.

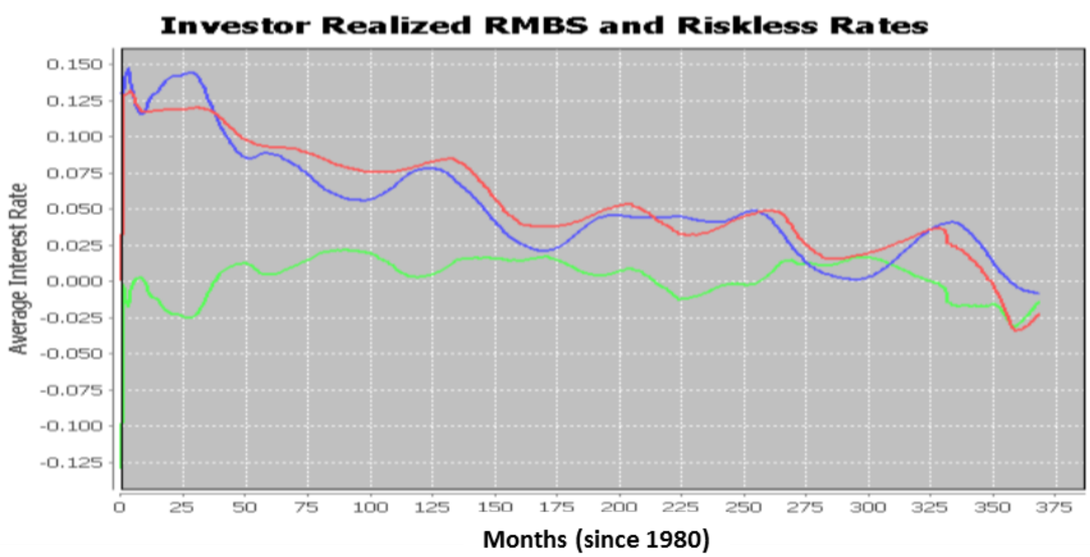



**Figure 56 Rates of return for RMBS shares and a riskless asset. The blue line represents the riskless interest rate investors face (smoothed over a few months). The red line represents the realized rate of return that investors received on RMBS shares. The green line measures the difference in the two lines.**

Thirdly, I wanted to investigate the effect of the RMBS market on financial institutions. Therefore, I ran the model both with and without the RMBS market. In the case of no RMBS market, financial institutions simply hold mortgages in their portfolio rather than creating asset backed securities out of them. I wanted to understand how the RMBS market affected financial institutions' ability to lend. I ran the model one hundred times for each case and compared the average number of houses sold per simulation for each case. I found, as expected, that the housing market is more liquid with an RMBS market. Specifically, about 33% more houses were sold in the model runs which included an RMBS market. Similarly, financial institutions approved about 60% more loans—both for home purchases and refinancing—to homeowners in the RMBS simulations. Finally, the average household debt service, as measured by debt to income ratio, was almost 70% higher (0.144 versus 0.085) in the simulations with an RMBS market.

This result, while in some sense intuitive, is not altogether obvious. Consider that in the RMBS case, some of the default risk is placed on investors, mitigating the effects of default on financial institutions. Similarly, some of the gains in loans are captured by investors in the RMBS case, mitigating the lender profit in times with low defaults. In the non-RMBS case, financial institutions' fortunes are more closely tied to homeowners' fortunes. It might seem that this would produce larger house price bubbles since the financial institutions asset sheets grow faster in good times when they are not sharing profit with investors. However, this asset buildup is in illiquid mortgage loans, whereas in the RMBS case, financial institutions are able to turn mortgages into liquid assets quickly, supporting issuances of new loans. This mechanism is dominant in fueling housing bubbles. See, for example, in Figure 57 where the house price index in the non-RMBS case grows to only a little more than 1.4 rather than above 2 in the RMBS case.

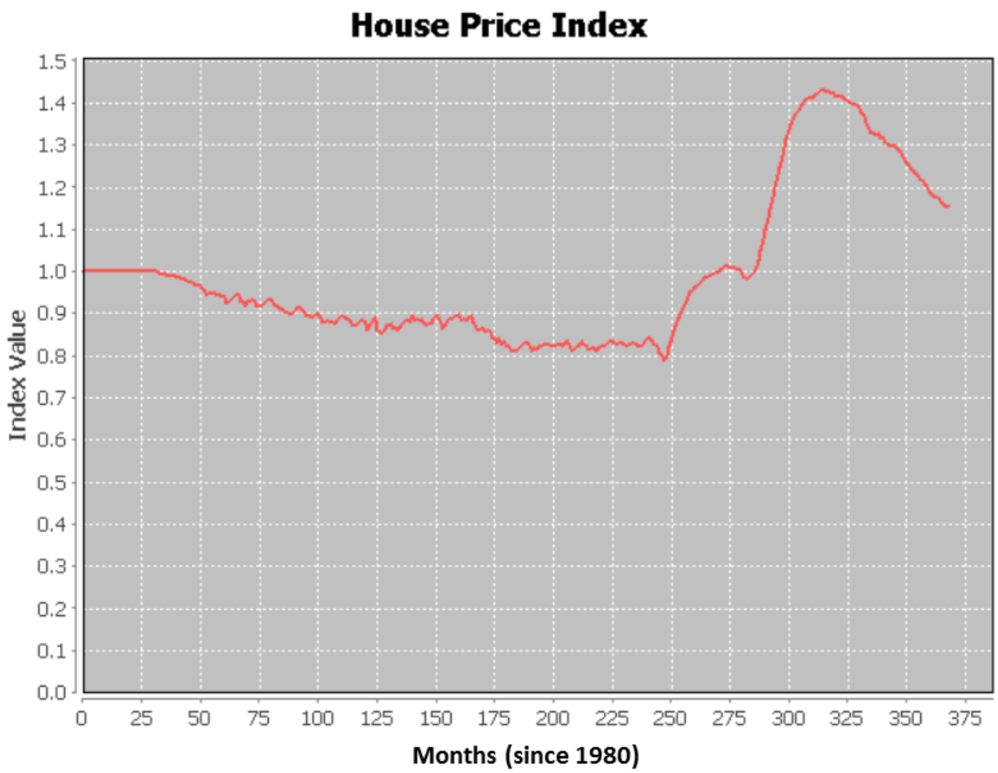



**Figure 57 House Price Index without RMBS market.**

Hence, the model suggests that the RMBS market causes the housing market and financial institutions lending in this market to be less stable. This result matches many hypotheses regarding the cause of the financial crisis. On the other hand, the mechanism that caused these large bubbles is not—as some have suggested—a decrease in lending standards due to an adverse selection problem emanating from the relationship between investors and financial institutions. Instead, it is that securitization provides financial institutions ready access to liquid assets to fuel more lending. This increases the magnitude of booms and busts is a mechanism similar to Geanakoplos's (2009) leverage cycle. However, two main shortcomings of the model—the unsophisticated RMBS market and the fact that financial institutions do not borrow money, somewhat altering the effect that changes in central bank rates have on the banking sector—make any conclusions from these results hard to draw.

### 6.5. Discussion of the RMBS-Housing Model

In this chapter, I presented a model of the financial crisis linking the housing market and the RMBS market. This model, I believe, contains many of the essential features needed to study the causes of the financial crisis. Moreover, even in its initial state it matches some stylized facts of the crisis well. However, there are clearly a number of elements that need to be added to the model. In this section, I will discuss some of them.

First, as noted several times, the RMBS market is too simplistic. Investors simply spend all their money buying RMBS shares, which are priced only based on the valuations investors have for RMBSes and the principal value of the underlying mortgages. These securities are not traded in subsequent timesteps. However, there are ample models to draw on in agent-based finance for constructing a more realistic model. For example, LeBaron (2001) provides a nice structure for agents building a portfolio of a risky and riskless assets. Although it might be desirable to use a different specification for agent's expectations than was used in that paper (e.g., such as the one in Hoffman et al. (2007) or Alfarano and Lux (2007)), the LeBaron setup could be used.

Secondly, another major concern is that financial institutions lend all money from cash. Therefore, if the central bank's interest rate increases, there is really no reason for financial institutions to increase their rates since they do not borrow at the central bank rate. However, since financial institutions do raise their rates in the model, they simply make more money when the interest rates are higher and less when interest rates are lower. This has the effect of applying counter pressure to a financial crisis. When interest rates increase and households default, financial institutions make the money back through increased profit from those higher interest loans that homeowners do repay. This dynamic can be remedied by a more detailed representation of shadowing banking sector.

Thirdly, there is no change in lending standards throughout the model. Archer and Smith (2010) report that mortgage lending standards decreased during the buildup of the housing bubble. Similarly, many have used this idea as part of their hypotheses for the causes of the financial crisis, especially the proponents of the "originate to distribute" hypothesis. To remedy this, lending standards should depend on the likelihood that a loan can be profitably sold as an RMBS, which in turn might depend on investors' expectations of RMBS performance, which, as shown in Figure 56, increases during the bubble.

Fourthly, once these improvements are in place, it will be important to increase the similarity of the model's input data with reality. That is, house values, income, wealth, and financial institution size should have roughly correct distributions versus actual data. Moreover, the relative number and size of these agents should be in the right proportions. There are doubtless other parameters that will need to be researched and based on real data, such as various factors that influence lending, refinance, and default decisions.

Finally, it is still an open question to me whether the real economy is important to include in this model. Clearly, if the purpose is to understand how havoc in the financial sector could double unemployment, the real economy would be essential. Of course, explaining the effects on the real economy is a long term goal of this research, but it is not a short term goal. The short term goal is to determine how it could be the case a 30% decline in house prices could cause over $1 trillion dollar losses to the financial sector. It is not obvious to me if the real economy is involved in that process.

However even with these shortcomings, the model in this chapter provides promise in shedding light on the causes of the financial crisis that began in 2007. It links the housing market to the RMBS market and attempts to explain how a drop in house price could to lead to huge losses in investor wealth. Currently, the model produces some stylized facts of the crisis, but clearly needs more work. As the model improves, it will be interesting to see which hypothesis regarding the origins of the crisis is most supported by the model's behavior.

# 7. DISCUSSION AND CONCLUSION

The work in this dissertation contributed to three research areas: understanding the underlying causes of the housing crisis, demonstrating the ability of ABMs to generate important macro phenomena, and improving ABM methodology. This concluding chapter summarizes the results in each of these areas and describes avenues for future research.

## 7.1. Investigating the Housing Crisis

At the start of the dissertation, I listed a number commonly cited causes of the housing crisis. These included leverage (Geanakoplos 2010, Haughwout et al. 2011), lending standards (Duca et al. 2011, Mian and Sufi 2009), changes in expectations (Hott 2009, Case and Shiller 2003), adjustable rate loans (Liebowitz 2009), inflows of foreign savings (Bernanke 2009), interest rates and associated refinance (Khandani et al. 2009), too little regulation (Gorton et al. 2010, Pozsar et al. 2010), mortgage backed securities (Levitin and Wachter 2012), and a banking panic (Gorton 2012). Although "causality" is a difficult concept to define, for the purpose of policy proscriptions, it is enough to show the counterfactual component. I.e., if a particular element were not present, can we show the housing crisis would not have occurred (see Shalizi 2016 chapter 22 for a discussion of the relationship between causality and counterfactuals)?

In general, the counterfactual exploration in Chapter 4 yielded that, according to the model, leverage and expectations were the primary drivers of the housing crisis. Importantly, refinances and ARM loans had little effect and completely removing these from the model did not affect the presence of the bubble or crash. This contrasts with some narratives of the crisis, notably the ratchet effect model of Khandani et al. (2009) and the mechanisms in Gorton's explanations (2008). Interest rates had a modest impact, with stable interest rates somewhat moderating the crisis, but not fully relieving it. Stable interest rates reinforced moderate LTV standards to produce the best outcome in terms of the counterfactuals. Other factors, such as norms governing the share of income going to housing, and seller behavior also influence the bubble. The housing plus RMBS model showed that increased velocity of lending made possible by securitization can increase the size of bubbles and make markets more fragile, increasing the likelihood of crashes.

## 7.2. Utility of Agent-Based Models

A second goal of this dissertation was to demonstrate the utility of agent-based models (ABMs) as a methodology for understanding large scale macro phenomena. The basis for this utility are ABM's ability to integrate large quantities of data from multiple sources, reproduce the detailed dynamics underlying macro phenomena, and act as a virtual laboratory for counterfactual analysis. I reviewed the latter aspect in the preceding subsection, but it is worth repeating that in comparison to other methods, such as mathematical models, ABMs produce a much richer environment for counterfactual analysis. Because the model does not need to be solved, it is easy to manipulate the rules in a possibly discontinuous way to implement a new policy and observe outcomes.

In the case of data use, Chapters 2 and 3 demonstrated how the model incorporated large quantities of data from various sources. Importantly, the model can handle heterogeneous data well. Take the example of the model's use of the empirical distribution of LTV at origination. The empirical distribution does not fit particularly well to any standard distribution, especially considering its multi-modality and other seemingly random features driven by tax and insurance laws. An ABM can simply draw from an empirically described set of histograms rather than require the distribution be converted into a functional form. Second, this distribution changes significantly both over time and with the size of the house purchased. The ABM can handle this heterogeneity easily by simply selecting the portion of the empirical distribution appropriate to the particular time slice and house price under consideration. Other modeling formalisms cannot handle such an ill-defined distribution and typically require the distribution be converted into a closed form expression that is invariant to local decision features, such as time and house size. Beyond this, I also showed that ABMs can integrate data from many sources, making even such a complex model as the one in this dissertation highly data-driven.

Finally, the third main argument for ABMs regards how they can match not only the key summary metrics, but also intermediate and distributional data. For this dissertation, the key summary metrics include housing market index, average house price, units sold, and average leverage. The housing market model did a reasonable job matching all these summary variables. Beyond these, the model matched the distribution of house prices and LTV well and also intermediate market variables such as average days on market, average ratio of sold price to original list price, foreclosure rates, delinquencies, and distribution of loan type. On the other hand, the model was not perfect, and many intermediate outputs, such as homeownership rate, matched only in general trend. However, even the imperfect model in this dissertation provides more insight into the underlying dynamics of the market than regression or analytic style models.

For more concrete comparison, Glaeser et al. (2012) provide a relevant mathematical model, extending the standard neoclassical user cost model of housing. This model is an equilibrium model built around the requirement that the marginal consumer should be indifferent between renting and owning. The authors pack many factors into the cost of housing, including expectation of increases in house prices, changes in interest rates, etc. The Glaeser et al. model is powerful in the sense that with a few equations, the authors can quantify the impact of changes in variables (e.g., downpayment requirements, interest rates, approval rates) and remark on the relevant importance of each. In fact, they find that none of the standard hypotheses of the crisis fully explain the crisis—individually or in combination. The authors back up their study with an empirical regression analysis that provides support to the theoretical results.

However, there are a few limitations to this type of analysis. For example, there are no time dynamics in this model. Therefore, theories with a narrative quality, such as the ratchet effect from Khandani et al. (2009) or Gorton's (2008) subprime refinance narrative cannot be tested because these rely on interest rate or lending standard changes paired with a particular state of the world. For example, in Khandani et al.'s model, homeowners first ratchet up leverage (facilitated by lowering interest rates, house price appreciation, and ease of refinance), creating a particular fragile state of the world in which a small change to interest rates or lending standards can have a big effect. However, the Glaeser et al. model only considers how changes in interest rates affect the decision of the marginal buyer, not how those interest rates affect the demand and supply of the market as a whole nor how these effects cascade into changes in default, refinance, and move rates. Because ABMs compute state changes and store history, an ABM can replicate and test narrative theories. In fact, Khandani et al.'s model is essentially an ABM, albeit one much less comprehensive than the ones in this dissertation.

A second major limitation of the Glaeser et al. (2012) model stems directly from its parsimony. The model does not include much heterogeneity because this would make the model intractable—and even infeasible to even transcribe in equation form. Similarly, the model cannot reproduce nuances of housing markets, such as market frictions or complex interactions between participants in the market. ABMs, instantiated in object oriented programming, naturally support nuances such as heterogeneity.

However, even given these strengths, there is much work to do to improve the utility of ABMs. Other modeling paradigms have significant advantages over ABMs. Analytic models are more parsimonious than ABMs and have provable properties. Often their parsimony allows them to be communicated more easily, and their results are crisper. Critics of ABMs charge they are too ad-hoc and too opaque. The results might hinge on some coding decision buried in source code that is unobservable to reviewers. The next subsection delves deeper into this dissertation's contribution to improving ABM methodology and avenues for future research in this area.

## 7.3. Agent Based Modeling Methodology

In this dissertation, I presented a housing market ABM, and in so doing, I followed several methodological principles. In this section, I talk more deliberately about three of these: model scaling, sensitivity analysis, and architectural design.

Model scaling refers to the ratio of the number of entities being modeled to the number of agents in a model. The housing market ABM contains one agent type representing households, and there are about 2 million households in the Washington DC MSA (this number of course changes over the course of the simulation). Typically, the lower the scaling factor (as long as it is $\geq 1$) the better the model fits the data, the less model produces excess variability due to random variations, and the slower the model runs. Even with breakthroughs in computing power, reality-scale models can take a long time to execute, making it difficult to conduct analyses that contain many runs, such as the sensitivity analyses in Chapter 5. Therefore, there is a question whether reality-scale models (i.e., scaling factor = 1) are necessary and if not, what scale should be used?

In Chapter 4, I presented a methodology to determine the appropriate scale at which to run model analyses. I determined an overall model metric and then ran the model repeatedly at various scales. Eventually (around a scaling factor of 10), reducing the scaling factor did not change the average or variance of this overall metric by any noticeable amount. That result provided evidence that it was not necessary to run the counterfactual analyses at a scale lower than 10. Although the methodology is relatively simple, it can be a useful way to answer the scaling factor question and should be conducted before embarking on explorations and analyses with an ABM.

The sensitivity analysis in Chapter 5 represents another important methodology presented in this dissertation. Often, criticisms about ABMs with regard to their opacity, brittleness, and dependency on arbitrary modeling decisions can be resolved through this type of analysis. First, a parametric sensitivity analysis—i.e., one focusing on the input parameters of the model—addresses the question of model brittleness (i.e., how dependent are the results on the precise choice of parameters) and also points the modeler to which parameters must be carefully chosen and justified. For example, the Chapter 5 model has the somewhat arbitrarily chosen value of eight for the number of similar quality recently sold houses (i.e., comparable houses) sellers consider when determining an initial list price. I showed that the model is not sensitive to the choice of this value. On the other hand, the model is a bit more sensitive to how far back in time sellers look for those comparable houses. The sensitivity analysis directs modelers' attention toward parameters that are more influential and also answers criticisms about the seemingly arbitrary choice of some of the parameters.

However, more than just a parameter sensitivity analysis, it is important to also test the sensitivity of model rules, which I call a structural sensitivity analysis. Behavioral rules are typically dependent on theory or some empirical results that are not exactly a match for their use in the model. Moreover, theories are often underspecified and there might be competing theories or empirical results that inform rule construction. For example, it seems plausible that expectations of house price appreciation might deter a household from defaulting, but it is difficult to find empirical justification for this hypothesis. In Chapter 5, I showed that when considering two plausible default rules (one non-linear based solely on LTV and the other linear based on both LTV and expectations), the model performed similarly and is not sensitive to this choice. On the other hand, I showed that the model is sensitive to some rule choices, such as how sellers set their initial list price. Again, the sensitivity analysis directs modelers' attention towards rule choices that are most influential and also answers criticisms about the seemingly arbitrary choice of some rules. Future work on the housing market model should expand this structural sensitivity analysis to all of the rules in the model.

Finally, to enable the structural sensitivity just described—and also to increase transparency of model assumptions—it is important to separate behavioral rules from the model execution flow. In the housing market model, I demonstrated this design. For example, the household agent class encodes only the general process through which agents complete a time step—i.e., receiving income, consuming, deciding whether to refinance or default, etc. However, the actual behavioral rules reside in a separate class called HouseholdDecisionSupport. This class contains a set of rules that map to the different household decisions. Due to this design, it is natural to create multiple versions of each of these rules and assign a specific version to each household. The final piece of architecture is a configuration class that governs which rules are active in a particular simulation and how to allocate the rules to agents. This makes it easy to test different rules and rule mixes in the simulation and conduct the structural sensitivity analyses as described in this subsection.

Future research in ABM methodology should continue to focus on addressing the central criticism of ABMs—that they are opaque and ad hoc, and it is difficult to determine the extent to which model results emanate from a coding idiosyncrasy or specific parameter. Several elements of this dissertation provide paths for addressing this concern, including the heavy grounding in empirical data and the model sensitivity analysis. Further, constructing models to explicitly isolate structurally uncertain aspects, such as the behavioral rules, is a key design element that reduces model opacity and allows modelers to quantify and communicate the model's sensitivity to these elements.

## 7.4. Future Research

Future research on the housing market model should move down three paths: model improvement, application to a second MSA, and more in-depth counterfactual evaluation. First, there are clearly inadequacies in the model, and the model needs continual refinement of rules and input data. The Chapter 5 model provided a great start along this path with improved data (swapping out LoanPerformance for CoreLogic) and calibration of the various modules independently based on data outside the model. The outcome of this effort was a more principled model, but which fit the output data less well. Future iterations should continue down this path and identify areas in which the model is lacking and whose inclusion might bring the model's outputs more into line with historical data.

For example, there is no spatial component in the model, but the spatial distribution of houses and diffusion of trends along those lines is clearly important. The housing crisis hit the outer suburbs of Washington DC much worse than the inner suburbs. Imbalances in supply and demand—while not acute overall—might have played a larger role in some of these outer areas which were rapidly developed during the boom. Moreover, Goodstein et al. (2016) provide evidence that the probability of strategic default is influenced by rate of strategic default in a homeowner's locality. Future iterations of the housing market model should investigate these spatial contagion processes.

Another clear area of extension is the banking sector, and the model in Chapter 6 describes one foray down that line. An obvious future task would be to integrate pieces of the Chapter 6 model into the base housing market model branch. Of course, there is much less data to support the model in Chapter 6 so this would pose a challenge given the heavy use of data in the base model. Additionally, even the Chapter 6 model lacks Government Sponsored Entities (GSE) such as Freddie Mac or Fannie Mae. The ironclad guarantees of GSE securitized loans greatly increased demand for securitized mortgages, which in turn increased mortgage securitization. As argued in Chapter 6, securitization increased the supply of capital to lenders, increasing the velocity of lending leading to increased market instability. Thus, including GSEs is a natural path of extension for the Chapter 6 model.

Another area of model improvement is in data preparation. As noted in previous chapters, the data used in the model does not precisely align with how the model uses the data. For example, the team used actual expenditure data to calibrate desired expenditure calculations, and actual loan data was used in setting parameters in the loan approval process. Methods to account for the mismatch in data should be investigated. Moreover, some aspects of the model seem not to function adequately. On the one hand, refinances might not have played much of a role in the crisis, but on the other hand, the model's handling of refinances might have been poor. Further study is needed to sort out that question.

Beyond just model improvements, another avenue for future research is application to a second geographical region. Because the model has been developed and evaluated for the Washington DC MSA, there is a danger that the team overfit the model to the DC region. Successful application of the model to a second MSA would both provide more confidence in the model and facilitate the extraction of general insights about housing markets. In the far future, a model that simulated many key regions at once, allowing for spillover effects between the regions would also add fidelity to the model.

A final avenue for future research would be to expand the methodology of counterfactual analysis. This analysis extracts insights from the model that inform policy decisions. The counterfactual analysis in this dissertation and in many ABM research is exploratory and somewhat ad-hoc. Future research should define a clear methodology for use of ABMs as virtual laboratories using design of experiment type of approaches, similar to those in the real world experiments.

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