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An Agent-Based Model of a Metropolitan Housing Market

Linking Micro-Level Behavior to Macro-Level
Analysis

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Problem Description

The purpose of this thesis is to develop an agent-based model (ABM) of a metropolitan housing market. An ABM is a computational model where the micro-level behavior of agents is simulated in order to analyse macro-level emergent phenomena. While this approach is commonly applied in fields such as biology, the literature on ABMs in economics is limited. On the topic of modelling the housing market, only a handful attempts exist.

The standard models of the housing market, employing regression techniques or theoretic concepts of equilibrium, failed to predict the boom and bust in the US market leading up to the world-wide financial crisis. These models are often fitted to past data or assume hyper rational, homogeneous agents and may therefore be inadequate when analysing a market bubble. Moreover, they seldom provide insights to the effects of macroeconomic policy. Agent-based modelling is a far more flexible technique, allowing for heterogeneous agents and without the assumption of a predetermined equilibrium state. Hence, an ABM might serve as an alternative to standard models.

The goal of this thesis is to implement an ABM of a housing market and perform simulations involving the effect of macroeconomic shocks and policy-making. The model is instantiated to match conditions of a metropolitan area, and is evaluated on historical data from this area. An important objective of the thesis is to assess whether an ABM can provide insights to the housing market that standard models cannot.

Preface

This Master Thesis is the final work required to obtain a Master of Science degree with specialization in Managerial Economics and Operations Research at the Department of Industrial Economics and Technology Management at the Norwegian University of Science and Technology (NTNU).

The choice of topic for this thesis was motivated by an eagerness to explore the power of agent-based modelling, a relatively new approach to simulation. The housing market, with its complex dynamics and importance to the larger macroeconomy, was an interesting subject for modelling. I have truly enjoyed working on this thesis and hope to get the opportunity to work with similar topics in the future.

I would like to thank my supervisor, Associate Professor Einar Belsom, for constructive discussions and assistance throughout the work. Without his invaluable input, the work on this thesis would surely have been less rewarding.

Trondheim, 20th of June, 2016

Sarah Ustvedt

Abstract

In this thesis, an agent-based model (ABM) of a metropolitan housing market is developed. ABMs are computational models simulating interactions between autonomous agents, and are built bottom-up by defining these agents on the micro-level. The ABM of this thesis is intended to match the market of the Norwegian capital, Oslo, with behavioral rules governed by historical data. The main agents of the model are households who engage in decisions such as moving and purchasing dwellings as investments. Exogenous variables of the model include the interest and unemployment rates, housing construction and immigration. Endogenous variables, which emerge as a result of agent interactions, are for instance the housing price, debt of households and home-ownership rate.

An important component of the ABM presented in this work is the defined market transaction process, where bidding rounds are held in order to clear the market. Further, households are assigned ordinal housing preference functions, which are applied to determine the sequence of bidding rounds the households participate in. Compared to the majority of literature on ABMs of the housing market, where all households prefer the same dwellings, this provides the model with more heterogeneous agents. Another feature of the ABM is that it is spatial. By applying Geographical Information System (GIS) data of Oslo, the dwellings in the model are placed in a 2-dimensional grid with borders representing the city's districts. This makes it possible to analyse price development in different geographical areas of the city.

The model is shown to generate output conforming well to historical data. Interesting observations include a higher growth of prices in central districts than in the suburbs, attributed to the high immigration of young households.

Three different counterfactual experiments are performed, in order to evaluate the effect of policy modifications and shocks to the model. First, tightening of the bank's lending policy through debt-to-income (DTI) and loan-to-value (LTV) limits is shown to have a stagnating impact on price development. Further, removing tax deduction of interest expenses yields a reduced price growth. Finally, an experiment testing how the market would respond to an interest rate shock is performed. A significant fall in prices and reduction in the growth of household debt is shown to be among the results.

Sammendrag

I denne oppgaven utvikles en agent-basert modell (ABM) av boligmarkedet i Oslo. Agent-baserte modeller simulerer interaksjonene mellom autonome agenter ved å definere dem på mikro-nivå. Agentene i modellen som presenteres i denne oppgaven er i hovedsak husholdninger som har egenskaper og regler for oppførsel basert på historiske data. Husholdningenes beslutninger involverer for eksempel flytting og investeringer i boligmarkedet. Eksogene variabler i modellen inkluderer rente, arbeidsledighet, boligbygging og innvandring. Endogene variabler, som utvikler seg som et resultat av agentenes interaksjoner, er eksempelvis boligpris, husholdningenes gjeld og eierskapsrate.

En viktig komponent i modellen som presenteres i dette arbeidet er reglene for transaksjoner i markedet, der budrunder holdes for å oppnå markedsklarering. Videre tildeles husholdninger ordinale preferansefunksjoner, som anvendes for å bestemme rekkefølgen på budrundene husholdningene deltar i. I forhold til den eksisterende litteraturen på ABMer av boligmarkedet, fører dette til en modell med mer heterogene agenter. En viktig egenskap ved modellen er at den er romlig. Ved å anvende geografisk informasjonssystem (GIS) data fra Oslo, er boligene i modellen plassert i et 2-dimensjonalt rutenett med grenser som representerer bydelene i Oslo. Dette gjør det mulig å analysere prisutvikling for de forskjellige geografiske områdene i byen.

Modellen vises å generere en fornuftig utvikling av de endogene variablene over simuleringsperioden. Interessante observasjoner som også underbygges av dataene er sterkere prisvekst i mer sentrale bydeler. Dette forklares med den høye innvandringen av unge husholdninger som foretrekker å bo i nærheten av sentrumskjernen.

Tre ulike eksperimenter utføres for å evaluere effekten av endringer i de makroøkonomiske forholdene. Først innstrammes bankenes utlånspraksis gjennom grenser på gjeldsgrad og egenkapitalkrav. Dette vises å ha en reduserende effekt på boligprisene. Videre fjernes skattefordelen av gjeld, noe som også resulterer i lavere prisvekst. Til slutt utføres et eksperiment for å teste hvordan markedet ville reagere på et hopp i renten. Et signifikant fall i boligprisene og en reduksjon i husholdningenes gjeldsvekst viser seg å være blant resultatene.

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Chapter 1

Introduction

The housing market is complex, characterized by a fixed short term stock, heterogeneous goods, high transaction costs and time delays. It is a market with goods that can serve for both consumption and investment purposes and differs from many other markets in the diverse characteristics of its participants. Unlike the stock market, where investment decisions are mainly made by professionals, households are the main players in the housing market.

The fact that housing is both a consumer and investment good could explain why the market for housing often is the most leveraged market in a country's economy. Leverage makes higher standards affordable, but also increases profits when prices rise. While developments in the housing market often are explained by fundamental factors such as interest rate and unemployment, households have been shown to possess bounded rationality, leading to phenomena such as herding. In a housing bubble, or a steep rise and subsequent fall in housing prices, the belief that prices will rise in the future has driven prices and led to over-investment.

In all countries, the housing market plays an integral role in the larger economy. While macroeconomic developments are determinants of housing prices, a downturn in the housing market can end up threatening an entire financial system. In 2009, the world witnessed the worst global post war recession, with numerous affected countries and a significant decline in World GDP per capita. It was the financial crisis, triggered by a burst in the US housing bubble, which lay the foundation for this recession.

Norway has also experienced the dynamics between the housing market and the rest

of the economy. After a fall in the oil price towards the end of the 1980s, several factors including increased unemployment led to a significant fall in housing prices.¹ In the preceding years, liberalization of credit markets with low capital requirements had gradually raised the credit risk of many Norwegian banks. With decreasing value of the assets held as security for issued mortgages, many banks experienced significant loss rates. Several of the largest commercial banks were nationalized in order to avoid bankruptcy.² During the last 20 years, the housing prices in Norway have increased steadily. However, after the recent oil price decline, unemployment rates have begun to rise and many economists have expressed their concerns of a new crisis.

Seeing how sensitive the economy is to the housing market, continuous efforts are made to construct macroeconomic models explaining the variations in prices. In Norway, institutions such as the Central Bank and Statistics Norway have developed numerous such models, often using time series analysis on variables like real income, unemployment rate and interest rate. These models are then applied to make macroeconomic prognoses based on estimated development of the explanatory variables. For the Central Bank, these models are essential in order to predict how new policies will affect economic stability.

The housing booms and busts in Norway during the 1980s and in the US between 2000 and 2005 are both evidence that traditional macroeconomic models can fail to forecast economic crises. While factors such as irrational, heterogeneous individuals in retrospect are considered important factors generating these crises, standard macroeconomic models assume rational, all-knowing agents. In addition, theoretical models rely heavily on the notion of equilibrium, where markets clear. This assumption is not necessarily valid during a crisis. Finally, empirical forecasting models based on time series analysis, are subject to the *Lucas critique* - that the effect of macroeconomic policy cannot be inferred using models based on historical data (Lucas, 1976).

In order to address the weaknesses of the standard models, alternative modelling techniques have been proposed. Agent-based modelling, a micro approach where heterogeneous agents are assigned behavioral rules simulated in a computer program, introduces flexibility not present in the majority of current models (Macal and North, 2010). While the literature concerning these models are mainly in the field of biology, in recent years, the research within economics has increased significantly. Despite showing promising

¹An analysis of the past housing bubble in Norway is given by Tranøy (2008).

²See for instance Moe et al. (2004) for a thorough investigation of the Norwegian banking crisis.

results, there have been limited attempts to apply agent-based modelling to the housing market. To date, main contributions include models proposed by Erlingsson et al. (2012), Geanakoplos et al. (2012) and Ge (2013). The intention of these models is to identify which factors were determinants of the housing bubble and burst leading up to the recent financial crisis. Under the current uncertain conditions of the Norwegian economy, there is no doubt that such a model could provide important insights to future developments.

This thesis presents an agent-based model (ABM) for the housing market, fit to Norwegian conditions. Based on historical data from the city of Oslo, the model is spatial, incorporating the different districts of the capital. Due to computational requirements, the model simulates a small-scale version of the Norwegian city with around 3000 agents (while the actual number of households is nearly 300 000).

Using results from existing literature on household preferences and the moving process, household agents are assigned interaction patterns and numerous simulations are run. An important contribution of this work to the literature concerning housing market ABMs is the market transaction process, where a bidding process is applied to reach market clearing. Further, the model is spatial, so agents interact in a 2-dimensional grid in the simulation.

Two different types of simulations are performed in order to analyse the developed model. First, the model is shown to produce output conforming to the empirical evidence of factors such as housing prices and household debt. After the model has been evaluated, counterfactual experiments are performed. In these simulations, the effects of a tighter lending policy, removal of tax deduction and an interest rate shock are analysed.

The thesis is structured as follows: in Chapter 2, some standard economic models of the housing market are presented. Chapter 3 provides a literature review of agent-based modelling, with focus on the applications in economics. The data sets and software used for simulation is described in Chapter 4, while the developed ABM is presented in detail in Chapter 5. Chapter 6 briefly describes how the ABM is implemented, including the choice of software and file organization. Further, Chapter 7 gives an overview of the simulations performed, and the results from these simulations are discussed in Chapter 8. Finally, in Chapter 9, concluding remarks are given indicating areas needing further work.

Chapter 2

Standard Models of the Housing Market

In this chapter, an overview of standard models of the housing market is given. This will lay the foundation when analysing the properties of the developed ABM. The standard models can roughly be divided in three different groups. In Section 2.1, theoretical models of the housing market are discussed, while Section 2.2 gives an introduction to macroeconometric models. Finally, a brief description of Dynamic Stochastic General Equilibrium (DSGE) models is given in Section 2.3.

2.1 Theoretical Models

Theoretical models of the housing market assume that housing prices can be determined by the intersection of supply and demand functions. The majority of these models simulate a homogeneous market with free competition. Often, such models are used as a starting point for econometric modelling. In this section, some approaches to constructing the supply and demand functions are presented. In addition, the equilibrium price in different time horizons is discussed.

2.1.1 Demand in the Housing Market

Providing the demand in the housing market are pure investors, pure consumers and those who are both investors and consumers. The pure investors consider housing an alternative to the stock market and rent out the properties they own to households. The pure consumers are the households who rent a property and live in it. Households who are both investors and consumers, buy a house seeking to satisfy their consumer needs while also maximising the expected return on the capital they have available.

Among authors presenting a theoretical demand function are Jacobsen and Naug (2004a). They focus on the demand for housing as both a consumption and investment good, and assume that this demand is proportional to total demand for housing. In their model, demand for housing (H^D) is a function of the living cost for an owner (V), the price index for other goods (P), the living cost for a renter (HL), household disposable real income (Y) and a vector of fundamental factors (X):

$$H^D = f\left(\frac{V}{P}, \frac{V}{HL}, Y, X\right) \quad (2.1)$$

The authors also assume that the partial derivatives of f with respect to $\frac{V}{P}$ and $\frac{V}{HL}$ are negative,

$$\frac{\partial f}{\partial\left(\frac{V}{P}\right)} < 0 \quad (2.2)$$

$$\frac{\partial f}{\partial\left(\frac{V}{HL}\right)} < 0 \quad (2.3)$$

This means that increase in the cost of owning a dwelling relative to the cost of renting or the price index for other goods, decreases demand for owning. In addition, the partial derivative of f with respect to Y is assumed to be positive,

$$\frac{\partial f}{\partial Y} > 0 \quad (2.4)$$

An increase in household disposable real income therefore leads to an increase in demand. Further, Jacobsen and Naug (2004a), express the real living cost for owners, $\frac{V}{P}$,

as a function of the price for an average dwelling, marginal tax on capital gains and expenses, expected inflation and expected growth in housing prices. The real income, Y is defined as a function of the nominal disposable income, the price index for other goods, cost of renting and the average price of dwellings. Based on these theoretical equations, the authors continue by fitting an empirical model for the development of housing prices.

The demand function developed by Jacobsen and Naug (2004a) is just one of numerous theoretical frameworks that can be applied for the housing market. Other frameworks might highlight different variables as determinants of housing demand. For instance, Ericsson et al. (1985) construct a separate demand function for new constructions depending on variables such as population, income, interest rate and relative price of new to second-hand housing.

2.1.2 Supply in the Housing Market

On the supply side of the market are the developers constructing new housing and the renovators supplying refurbished housing to the market. Ericsson et al. (1985) suggests a simple theoretic model for the supply-side of the housing market. In this model, the supply of new constructions in a period is defined as function of the uncompleted dwellings in the previous time period, housing prices and construction costs. The housing supply in a period t (H_t) can be expressed by an equation involving the housing supply in the previous period (H_{t-1}), the rate of house destruction (δ_t), new constructions (C_t) and other sources of housing, for instance provided by the government (O_t):

$$H_t^s = (1 - \delta_t)H_{t-1} + C_t + O_t \quad (2.5)$$

In the short-run, C_t and O_t are small, and in many theoretic models the housing stock is therefore considered fixed, yielding a perfectly inelastic supply curve. Considering the long-run, it is often assumed that the supply of houses is perfectly elastic (Follain, 1979).

2.1.3 Equilibrium in the Short-Run and Long-Run

In the short-run, the housing stock can be considered fixed. According to Kongsrud (1997), if the short-run housing stock is denoted H^* , the equilibrium must then be defined by the point where the rate of substitution by the marginal consumer (RS^M) equals the cost of owning (CO):

$$RS^M(H^*) = CO \quad (2.6)$$

The cost of owning can then be expressed as a function of the real interest rate (R), the real housing price (RHP), the tax advantage (T), the expected real capital gains (CG) and maintenance costs (C):

$$CO = R * RHP - S - CG + C \quad (2.7)$$

By applying the expression for cost of owning in Equation 2.7 to Equation 2.6, the equilibrium real housing price becomes:

$$RHP = \frac{RS^M(H^*) + S + CG - C}{R} \quad (2.8)$$

This equilibrium is illustrated in Figure 2.1.1. In the long-run, assuming a perfectly competitive market, with no barriers to entry, the equilibrium is only affected by shifts in demand. However, this assumption might not hold in areas where land is scarce.

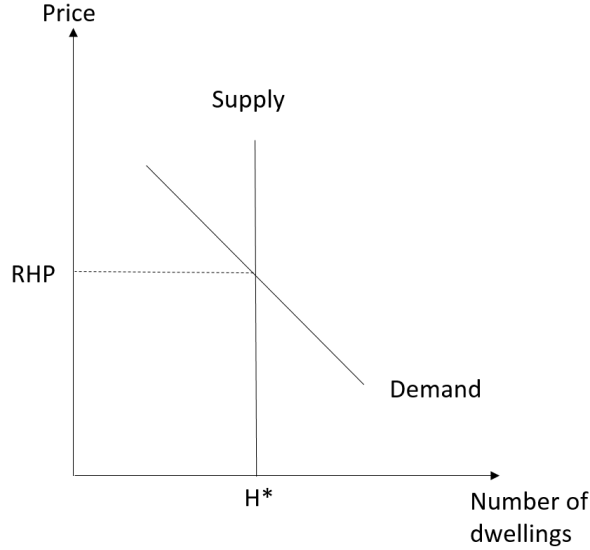


Figure 2.1.1: Short-term equilibrium (Kongsrud, 1997)

2.2 Macroeconometric Models

With access to historical records of macroeconomic variables like employment and interest rate, econometric methods can be applied to construct macroeconometric or empirical forecasting models of the housing market. Often, theoretical models as described in Section 2.1, lay guidelines for which variables to include. Jacobsen and Naug (2004a) apply the theoretical demand function presented in Section 2.1.1 to construct an empirical forecasting model. This model is based on quarterly data in the period 1990-2004 and expresses the long-run housing price as a function of the real interest rate (RRT), tax on capital gains and expenses (τ) unemployment rate (UR), income (I) and housing stock (HS), given in the following equation

$$Price = constant - 4.47 * RRT * (1 - \tau) - 0.45 * UR + 1.66 * I - 1.66 * HS \quad (2.9)$$

The short-run solution is similar to Equation 2.9, but includes a term for the expectations of households regarding the country's economy. In addition, the coefficient for unemployment and income is significantly lower, indicating that it takes time for

changes in unemployment and income to impact the housing market. According to the model, changes in the real interest rate will have a more significant impact in the short-run.

Many econometric models incorporate a whole economy and not just the housing market. For instance, the MODAG model, developed by Statistics Norway, is a large-scale econometric model for the entire Norwegian economy (Boug and Dyvi, 2008). The Ministry of Finance frequently apply this model to provide prognoses for future developments in the economy. The housing price relations in MODAG are based on a theoretical model where housing demand is a function of real disposable income, the cost of owning and the real interest rate. Housing supply is assumed to be a function similar to Equation 2.5 in the previous section, where new constructions (C_t) depends on building costs, residential lot costs and housing prices. Based on data from the period 1986-2005, the long-run solutions for the price of second-hand housing and new constructions is found to be:

$$pbs - pc = constant - 0.62 * k_{83} + 1.62 * (rc - pc) - 11.59 * RRT \quad (2.10)$$

$$j_c = constant + (pbs - pjks_{83}) \quad (2.11)$$

Where PBS is the price index for second-hand housing, PC represents consumption deflation, J_c is the initiated number of housing units, RC is household disposable income, RRT is real interest rate, K_{83} is total housing supply and $PJKS$ is index for construction costs used as proxy for price of new housing without lot. Small letters indicate that variables are on a logarithmic scale.

2.3 DSGE Models

An alternative to econometric and empirical forecasting models are Dynamic Stochastic General Equilibrium (DSGE) models. DSGE models were in part developed as a response to the critique towards traditional macroeconomic models for having limited predictive power. Instead of applying historical data to fit the model, a DSGE model is based on a microeconomic principles and is tailored towards evaluating the effect of policy making. Agents, corresponding to for instance households, firms and banks, are

assigned preference functions they seek to optimize. It is assumed that these agents are rational and make the optimal decision accounting for the decisions of all other agents. The equilibrium in the model is found by summing up all decisions from every agent and calculating the price that matches supply and demand.

While there exist a wide range of different types of DSGE models, the basic structure of such models include three main blocks; a demand block, a supply block and a monetary policy equation (Sbordone et al., 2010). These blocks are defined by sets of micro-founded equations involving assumptions about the economy's households, firms and the government. In each time period, these agents act and the market clears, reaching a temporary equilibrium. Random exogenous shocks are imposed to simulate the uncertainty in the development of the economy.

DSGE models are commonly applied to model the larger macroeconomy, however attempts directed towards the housing market in particular also exist. Iacoviello and Neri (2010) develop a DSGE model of the US economy including explicitly the price and stock of the housing market. They apply this model to study how shocks and frictions can explain developments in the housing market itself, but also to evaluate the impact of the market on the wider economy. In their model, households maximize over a function involving variables such as consumption and housing. Firms in the nonhousing sector produce their output using labor and capital, while the housing sector applies labor, capital, land and an intermediate input. The equilibrium conditions of the model involve new homes produced (IH_t), the housing stock (H_t), consumption (C_t), intermediate input ($k_{b,t}$), wholesale goods (Y_t), investment specific technology shocks ($A_{k,t}$), components of business investment ($IK_{c,t}$ and $IK_{h,t}$), adjustment costs for capital (ϕ_t) and a depreciation rate (δ_h), yielding the following equations:

$$C_t + \frac{IK_{c,t}}{A_{k,t}} + IK_{h,t} + k_{b,t} = Y_t - \phi_t \quad (2.12)$$

$$H_t - (1 - \delta_h)H_{t-1} = IH_t \quad (2.13)$$

In equation 2.12, total wholesale goods less adjustment cost for capital must equal the consumption, business investment and intermediate inputs. Equation 2.13 is intuitive, as it expresses the number of built homes as a function of the current housing stock less the dwellings not depreciated from the previous period.

A DSGE model is therefore simply a large set of equations, which are solved in each time period to calculate the equilibrium. Applying the defined equations for the agents and overall model, a Bayesian approach is often applied to fit the model to historical data.

Chapter 3

Review of Agent-Based Modelling

In this chapter a review of the literature concerning agent-based modelling is presented. As this modelling technique differs substantially from the methods discussed in Chapter 2, a thorough introduction to the subject is given in Section 3.1. In Section 3.2, the application of ABMs in the field of economics is discussed, while Section 3.3 gives an overview of existing models of the housing market.

3.1 Introduction to Agent-Based Modelling

An ABM is a computational model comprising of autonomous agents who interact with each other. The actions of these individual entities are simulated in order to record the aggregated effect on the whole system. Systems of interacting agents can take a wide range of different forms, from bacteria cultures to market places. Therefore, ABMs can be applied in numerous fields and simulate systems of only a few or thousands of agents.

In order to build an ABM, the first steps are to define the agents and their interaction rules. Hence, a key assumption for applying this modelling technique is that the system being simulated has agents whose attributes and interaction patterns can be explicitly defined. In addition, it must be assumed that it is possible to model the system from the bottom up. This is an important motivation for ABMs, namely that macro-level phenomena can emerge from micro-level behavior.

The agents of an ABM have individual goals and can have the ability to react and change their behavior throughout the simulation. They are presumed to act according to their own interests to reach this goal, which can be for instance reproduction or economic benefit (Axtell et al., 2003). Their behavior, which can be governed by heuristics or involve randomness, can develop if the model incorporates artificial intelligence methods like neural networks to facilitate learning (Bonabeau, 2002).

Bonabeau (2002) highlight three main advantages of ABMs. First, ABMs can capture emergent phenomena arising from micro-level behavior that can not be inferred by the systems' parts. In some cases, these phenomena can be counterintuitive and therefore provide new information about the system. The second advantage is that ABMs give a natural description of many systems. By this it is meant that an ABM will appear closer to reality than an alternative description using equations governing the dynamics. The final advantage is that ABMs are very flexible models. One can easily add agents, modify their level of description and complexity.

Many dynamical systems involve some form of spatial element. For instance, in a system of chemical reactions, atoms closer to each other measured in euclidean distance are more likely to interact. An ABM, defined by its agents and their behavior, can incorporate this spatial element by assigning attributes for location. With access to geographical data, an ABM can be calibrated to closely fit reality (Brown et al., 2005). Agents can be arranged in a two or three-dimensional grid and account for their position when executing an action. This makes it possible to model many real life systems very accurately.

Applications of agent-based modelling can be found in various research areas, simulating systems in for instance biology and social sciences. One of the first ABMs was a model of segregation, where coins and graph paper was applied rather than a computer implementation (Schelling, 1971). Based on the simulations, it was inferred that there was no simple correspondence between individual micro-level behavior and aggregated results, motivating further research on the topic. In a world with increasing access to data and computational power, ABMs have become popular in many fields. In the area of economics, ABMs have received special attention as standard models have proved to have significant shortcomings.

3.2 Applications in Economics

In economics, the development of ABMs has come as a response to the weaknesses of econometric and dynamic stochastic general equilibrium (DSGE) models. This is emphasized by Farmer and Foley (2009), who stress that standard models not only failed to predict the recent financial crisis, but also are unable to properly evaluate policies for recovery. However, the literature on ABMs in economics is still limited and seldom applied for policy making.

Leombruni and Richiardi (2005) investigate possible explanations for the low representation of agent-based modelling in top ranking economic journals. They identify two main reasons why ABMs are viewed with scepticism: the belief that they are (a) difficult to interpret and generalize, and (b) difficult to estimate. They end their investigation by concluding that the critique is ungrounded and that ABMs offer significant advantages to traditional analytical models.

One attempt to construct a large scale ABM of an economy is EURACE, which incorporates all EU countries (Deissenberg et al., 2008). In this model, there are three main types of agents: firms, households and banks. By defining regions, and locating each agent in one specific region, the model is spatial. The decision making process in this model is based on empirically observable behavior analysed in a wide range of literature. For instance, the purchasing and saving rules of households are based on results found in research on household behavior while firm behavior is determined by literature on heuristic managerial decision rules. EURACE has since its development been applied to simulate the effect of many economic policies like labour market liberalization.

ABMs can be applied for many purposes in the field of economics, and do not necessarily need to contain a whole economy like the EURACE model. One of the most active research areas are bottom-up modelling of markets, especially concerning the financial sector. Raberto et al. (2001) construct an artificial financial market with heterogeneous agents managing a portfolio of assets. They are able to reproduce several characteristics of financial time series like volatility clustering. A similar approach is taken by Lux and Marchesi (2000), who mainly consider the phenomena of volatility clustering - that large changes in return are clustered together. Other markets that have been modelled include the fish market (Kirman and Vriend, 2000), the electricity market (Weidlich and Veit, 2008) and the labor market (Chaturvedi et al., 2005).

3.3 Agent-Based Models of the Housing Market

While there are many examples of ABMs applied towards the financial market, fairly few have attempted to build an ABM of the housing market. As this market is characterized by a large set of heterogeneous agents, acting under limited information about each other, an ABM approach seems reasonable. While standard models are concerned with the equilibrium state of a system, we are often interested in the development outside this equilibrium state in the housing market. In order to explain busts and booms, an equilibrium model is not sufficient and we need tools that can describe a dynamic process. Important attributes in an ABM of the housing market are household preferences, life cycle, income, mortgage negotiation and the exchange process. When reviewing the current literature, it is therefore relevant to compare how different models have defined these components.

One of the most sophisticated attempts to simulate the housing market as an ABM is made by Geanakoplos et al. (2012) with details of the model given by Axtell et al. (2014). They apply micro data from 2.2 million households in the Washington D.C area to build a model seeking to explain the housing boom and bust of 1997-2009. By incorporating attributes such as household demographics, housing stocks, loan characteristics and market behavior, realistic agents are constructed. Household preferences are modelled by an expenditure rule based on income and lagged home appreciation. Instead of applying the common assumption that households spend a third of their income on housing, the model uses a function that better fits data and incorporates heterogeneity in household preferences. The income process is inspired by the work of Carroll (1997) and matched to income statistics. In the "Carroll Process", each household has a total income determined by a permanent and transitory shock. Denoting I_t as the total income in time period t , V_t the transitory shock in that time period, P_t as the permanent income, N_t a shock to permanent income and G the constant growth rate in permanent income, the stochastic process is defined as follows

$$\log(I_t) = \log(P_t) + \log(V_t) \tag{3.1}$$

$$\log(P_{t+1}) = \log(G) + \log(P_t) + \log(N_{t+1}) \tag{3.2}$$

$\log(V_t)$ and $\log(N_t)$ are assumed to be normally distributed with parameters fit to his-

torical data. In the model, mortgage negotiation is performed based on the maximum loan-to-value (LTV) set by the bank and debt-to-income (DTI) ratio, and again empirical distributions are applied to set appropriate loan type and interest rate. The exchange of houses is modelled by letting all households have a fixed probability of listing their house on the market based on the proportion of listed houses historically. If a household lists its house, it sets a price (P) based on average prices of houses of similar quality (\bar{p}), the average days on the market (DOM), the average sales price to original listing price (s) and a random noise parameter (ϵ), given by the following empirically fitted function

$$P = \exp[0.22 + 0.99 * \log(\bar{p}) + 0.22 \log(s) - 0.01 * \log(DOM) + \epsilon] \quad (3.3)$$

In every time period, homeless buyers are ranked based on the value of their expenditure function and buy the dwelling with the highest quality within their budget. If there are no available houses within their budget, the household turns to the rental market. Investors (or households owning more than one dwelling) are allowed to buy any remaining dwellings at the end of each time period.

Applying the described model, Geanakoplos et al. (2012) find evidence indicating that it was high leverage and not interest rate that led to the housing boom and bust. Similar results are found by Ge (2013), who also investigates the recent US housing bubble using an ABM. However, the two models differ significantly in terms of agent behavioral rules and characteristics. The model by Ge (2013) is spatial, so that houses are located in specific neighborhoods, which is an important determinant of housing price. The exchange of houses is modelled by introducing a real estate agent who matches bids and asks from households. Mortgage negotiation is a simple process where the bank announces maximum LTV, minimum DTI and interest rate giving equal conditions for all agents. The interest rate is based on the risk free rate and overall probability of default, so that the return complies with the law of one price.

Other authors who use agent-based modelling to determine the cause of housing bubbles are Erlingsson et al. (2012). Their model incorporates several markets including the labour, credit and housing market and is calibrated to fit empirical evidence from Iceland. Since the model includes the labor market, household income is determined endogenously through the demands of the firms which again depend on demand from consumption from households. In the housing market, households provide supply and

demand for housing based on an exogenous probability. If a household decides to sell its house, the house is listed on the market at a price based on the average housing price with a random markup. Housing exchange takes place through a market matching of the households who have listed and requested a house. In the mortgage negotiation, the bank decides to grant an application if (a) it can maintain its capital requirement according to the Basel II framework and (b) the fraction of total income (C^j) spent on housing (H^j) by a household is less than some maximum expenditure (β). Letting U^j denote the total cost related to a potential new mortgage, including interest and principal payments, the condition follows

$$\frac{H^j + U^j}{C^j} \leq \beta \tag{3.4}$$

Similarly to the two first models discussed, Erlingsson et al. (2012) illustrate that increasing β , or relaxing the lending constraint of the banks, leads to a boom in the house prices. In a later article based on the same model (Erlingsson et al., 2014) it is further shown that this boom can easily be followed by a recession, as higher leverage leads to a more unstable economy.

Chapter 4

Data Description

The data used to populate agents in the ABM developed in this thesis mainly originates from the records of Statistics Norway. Additionally, exogenous variables and historical data used for model validation is drawn from sources such as Real Estate Norway. As the housing market of the Norwegian capital, Oslo, is the environment being modelled, all data is intended to represent local conditions. The data available has often been aggregated into intervals, which are then used to draw agent attributes. When local data for Oslo is not available, country level records are applied and hoped to be a good approximation. A short presentation of the different data sets are given in the following.

4.1 Household and Housing Characteristics

Data on household demography, income, wealth and savings is drawn from Statistics Norway's registers on the Oslo population. The data is available on a yearly basis and given on interval level. Since the probability of having a certain income and wealth is conditional on for instance household age, drawing values unconditionally from the distributions would result in unrealistic households. Although the relevant conditional distributions do not exist in the registers, the median, conditional on household age and type, is available. When instantiating new households, it is therefore ensured that this mean is preserved in the synthetic population.

Statistics Norway record detailed data on characteristics of the Oslo housing stock and constructions. For each district in the capital, the number of dwellings by type is

available. In addition, the distribution of dwelling size conditional on dwelling type for the city on an aggregated level is recorded. For instance, the proportion of large dwellings is higher for the dwelling type "house" than "semi-detachable".

The unemployment rates, applied to determine the proportion of unemployed households in the simulation, are recorded monthly and obtained from Statistics Norway.

4.2 Real Estate and Mortgage Data

There are numerous sources with data on Norwegian housing sales. In this thesis, data from both Statistics Norway and Real Estate Norway is applied. From Statistics Norway, figures on the number of transactions by housing type and average square meter prices are obtained. This data is on city level and not for each individual district. Therefore, sales price indexes from Real Estate Norway, showing the development of prices in each district are used for analysis on district level.

The Financial Supervisory Authority of Norway publish yearly reports on issued mortgages on a country level.¹ Data on the distribution of LTV and DTI on newly issued mortgages is obtained from these reports. Further, the proportion of mortgages issued with an interest-only period can be found in these reports.

The interest rates applied in the simulation are obtained from Statistics Norway and based on newly issued mortgages in the entire country, given as the average rate on outstanding debt.

4.3 Geographic Information System (GIS) Data

In order to construct a spatial model, data on the geographical properties of the Norwegian capital is necessary. Data used to present spatial properties is often referred to as GIS data and can come in many different formats. In the developed ABM, the different districts of the city are important spatial elements. Therefore, the district borders should be represented in the model. This is achieved using the shapefile (vector data)

¹See for instance <http://www.finanstilsynet.no/no/Artikkelarkiv/Rapporter/2013/Finanstilsynets-boligglansundersokelse-hosten-2013/>

Chapter 5

An Agent-Based Model of the Housing Market

In this chapter, an ABM of a housing market is presented. The model is similar to those discussed in the literature review in some aspects, for instance in the representation of income development. However, it incorporates country specific agent interaction patterns from Norway, which has not been attempted to date in the literature. The choice of model architecture is based on existing research on areas such as household behavior and the housing market. Since the model attempts to represent Norwegian conditions, literature grounded in empirical evidence from Norway is preferred. The model is calibrated with data from the capital, Oslo, but could easily be extended to include the whole country. One of the intentions of the model is to evaluate how the agent-based approach performs compared to standard economic models of the housing market. Hopefully, it can serve as a more accurate alternative when performing forecasting and policy analysis.

The chapter is structured as follows: in Section 5.1 an overview of the model architecture and agents is presented. Agent attributes, for instance determining how households evolve over their life cycle, are given in Section 5.2, while Section 5.3 details how agents interact when negotiating for mortgages and moving between dwellings. Finally, the model execution is discussed in Section 5.4.

5.1 Model Overview

The ABM developed in this thesis is intended to simulate the market of a small city with the characteristics of the Norwegian capital, Oslo. Ideally, one household in the model should represent an actual household in Oslo. However, a simulation with a model of this size (nearly 300 000 households) would lead to long running times. Instead, a small scale version of the city is modelled with 3000 agents. This is chosen over creating a small scale version of the whole country as developments in the housing market in Norway differ substantially by area. For instance, while the housing prices in the capital rose by 9.2% in 2015, the prices in Stavanger (Norway's third largest city), fell by 8.1% during the same time period.¹ In an ABM representing the entire housing market of Norway, these regional differences in economic development would therefore need to be modelled. As this is not the focus of this thesis, it is more appropriate to consider a smaller component of the market.

5.1.1 Agents and Objects

The main agents and objects in the ABM are the households, the bank, dwellings and mortgages. Since only one bank is assumed to handle the mortgages, this bank is not actually implemented as an agent in the computer program running the simulation. Instead, mortgage applications are treated from the main code. However, for simplicity, the remaining description of the model is presented as if there was a bank object executing the code concerning the issue of mortgages. In Figure 5.1.1, a simplified class diagram with the agents and objects, their main attributes and methods is shown. The class diagram for the entire implementation is very extensive, and therefore not included.

Households

Households are chosen as agents instead of individuals as decisions related to housing mainly are taken by a household as a unit. Household attributes include the age of the oldest member and the household type, specifying whether the household has children.

¹See <https://www.ssb.no/priser-og-prisindekser/statistikker/bpi/kvartal/2016-01-13>

In each time period, households act according to set rules and update their internal attributes. Non of the household attributes are therefore constant throughout the simulation.

Dwellings

Dwellings can be owned by a household who lives in it or rented out to households who cannot afford to buy their own dwelling. When a dwelling has entered the model, it remains there until the end of the simulation. Dwellings do therefore not depreciate and are assumed to hold a constant quality. Further, the size of the dwelling is an important determinant when calculating its listing price. The ABM presented in this thesis is spatial, meaning that the dwellings have a specific location in a 2-dimensional grid throughout the simulation.

Mortgages

Mortgages are objects with attributes including the mortgage principle, its date of origin and maturity. They are linked to both households and dwellings and can only be linked to exactly one dwelling, and owned by exactly one household. Households can however own several mortgages, for instance if they have invested in additional dwellings. Mortgages are added to the model when a household buys a dwelling and it cannot finance it fully with its savings. After the bank has determined that the household is eligible for a mortgage, the mortgage is created and linked to the appropriate household and dwelling. A mortgage is only removed from the model when a household sells the dwelling it is linked to and uses the proceeds to pay it down, or it is payed down through monthly installments.

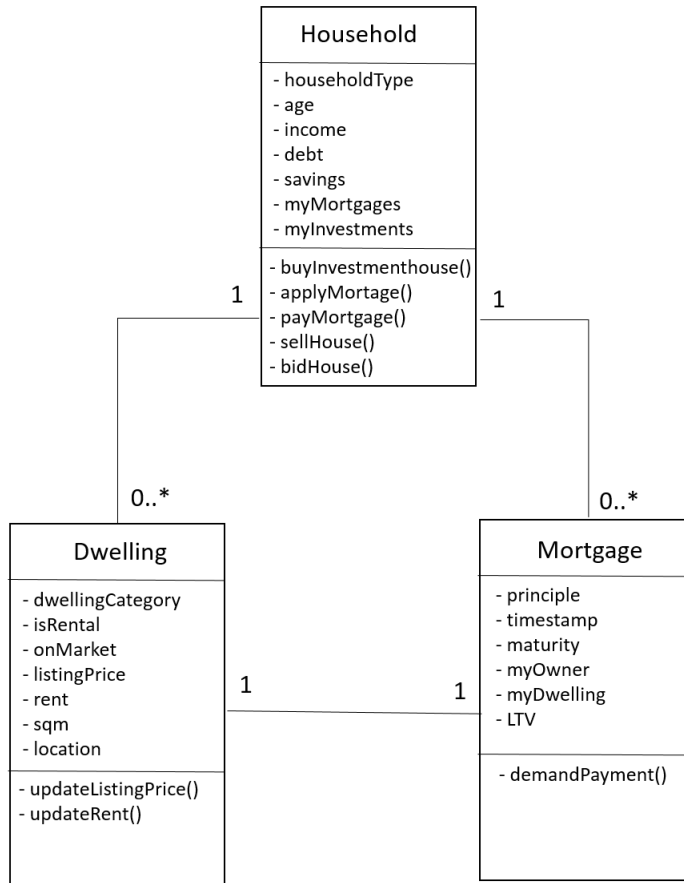


Figure 5.1.1: Simplified class diagram of the ABM

5.2 Household Attributes

Households are the main actors on the housing market and therefore need to be modelled carefully. In this section, the characteristics of households are described with focus on their heterogeneity. The data presented in Chapter 4 is applied to model the household life cycle, income and characteristics of houses. Each household agent in the model represents a household in a small-scale version of the city of Oslo and they should ideally have representative values for the different attributes. Therefore, methods to populate the model in a realistic manner are necessary.

5.2.1 Life Cycle and Demographics

Two types of household categories exist in the model, those with and those without children. In addition, each household has an "Age" attribute, representing the age of the oldest member of the household. Households are instantiated with an age and category so that the age distribution and the number of households with children in the model matches the actual distribution in Oslo during 2006. Both the category and age of a household are important variables in the income process and preference functions presented in following sections.

In the model, newborns do not create new household agents, as they are born into existing households. Instead, a certain proportion of the households without children, transition into households with children in each time period. Similarly, households with children can transition into households without children, reflecting that the oldest child has moved out. Below, the age dependent probability of having a child during a year of simulation is shown:

Table 5.2.1: Birth rate by age

Age	P_{age}^C
20-24	0.06
25-29	0.13
30-34	0.12
35-39	0.05
≥ 40	0

These probabilities are based on Statistics Norway's registers on number of newborns to households of different ages.² While these figures change slightly over time, they are assumed to take 2006 values for the entire simulation. The age of the youngest child in a household is incremented each year, and the child is assumed to move out when it is 18 years old.

In reality, a young adult creates a new household when it leaves its parents dwelling. In the model this is handled implicitly through net immigration and population growth. Each year a number of new households are instantiated, yielding an annual population growth equalling the historical growth in the Norwegian capital. A household only leaves the model when its age reaches 80.

²See Statistics Norway's Population Statistics at <https://www.ssb.no/en/befolkning>

5.2.2 Income Distribution and Process

The income of a household evolves through the household’s life cycle and can be simulated by some stochastic process. When running the model, it is preferable that the distribution of income among households matches the real distribution in Oslo in each time period. In Figure 5.2.1, plots of the distributions in 2006 and 2014 are shown. These histograms are based on aggregated data, but still convey important information about the nature of the underlying distribution. Dagsvik and Vatne (1999) argue that in fact, income follows a stable distribution³ and use micro data from Norwegian households to fit the parameters of this distribution. For simplicity, the log-normal distribution is applied to instantiate the households in the model. In order to assign households incomes that are reasonable with respect to household category and age, income cannot be drawn unconditionally from the overall income distribution of the population. Instead, N incomes are drawn from the distribution and assigned to the constructed households so that the conditional median income given household category is preserved. While it would naturally be simpler to construct one distribution for each household category, this data is not available for the required time period.

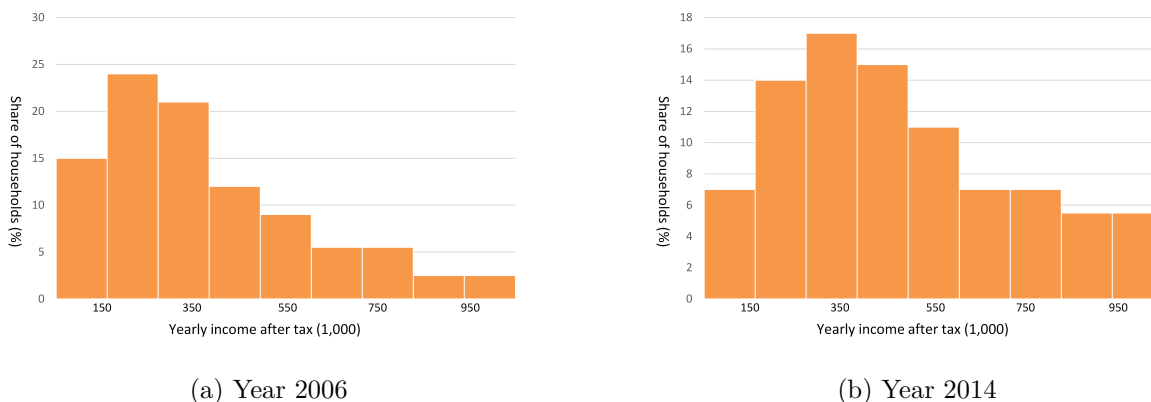


Figure 5.2.1: Income distribution for households in Oslo

In current literature, there are two main views on how the income process should be modelled. Guvenen (2009) name them the ”Restricted Income Profiles” (RIP) process and the ”Heterogeneous Income Profiles” (HIP) process. While the RIP process is characterized by a persistent shock component and a life-cycle component, the HIP process

³A distribution is stable if the linear combination of two copies of a random draw also follows the distribution.

is defined by shocks with less persistence and individual income profiles. The "Carroll Process", applied in the paper by Geanakoplos et al. (2012) can then be categorized as RIP, with total income determined by a permanent and transitory shock that does not depend on an individual income profile. While a significant number of authors have found support for the HIP process ⁴, an RIP process is applied in this thesis as it is more common in modelling income processes in economic models and also requires less computation.

Denoting $I_{h,t}$ as income by household h in period t , ϵ_t as a transitory shock, $Z_{h,t+1}$ as persistent innovations to income corresponding to for instance promotions, $G_{h,t}$ as the constant growth rate determined by household age in that time period and η_t as a persistent shock in income, the log of annual earnings in the model is given by

$$I_{h,t} = Z_{h,t} + \epsilon_t \quad (5.1)$$

$$Z_{h,t+1} = Z_{h,t} * (G_{h,t} + N_t) + \eta_{t+1} \quad (5.2)$$

Where $G_{h,t}$, or the life cycle growth rate depends on the age of the household in period t and is roughly based on analysis by Vestad (2014). A young household will experience high growth income, while older households have declining income development. When households reach retirement age, pension is assumed to equal the salary received at age 70:

$$G_{h,t} = \begin{cases} 1.1 & 20 \leq age_{h,t} \leq 29 \\ 1.05 & 30 \leq age_{h,t} \leq 59 \\ 0.95 & 60 \leq age_{h,t} \leq 69 \\ 1 & 70 \leq age_{h,t} \leq 80 \end{cases} \quad (5.3)$$

N_t is the recorded nominal average growth of incomes in period t . Based on estimations from both Carroll (1997) and Hall and Mishkin (1980), $\epsilon_t \sim \mathcal{N}(0, 0.32)$ and $\eta_t \sim \mathcal{N}(0, 0.37)$ when the Carroll process is assumed.⁵ Although these parameters have been fit to conditions in the US, they generated reasonable patterns for development

⁴See for instance Haider (2001), Baker (1997) and Guvenen (2009).

⁵Converted from thousands of dollars to thousands of Norwegian Krone using currency rate 1\$ = 8.27 NOK

in income and are therefore applied in the presented ABM. In Figure 5.2.2, the income distribution in year 2014 of a population with initial income drawn from the distribution in Figure 5.2.1a and income development governed by the described stochastic process is shown.

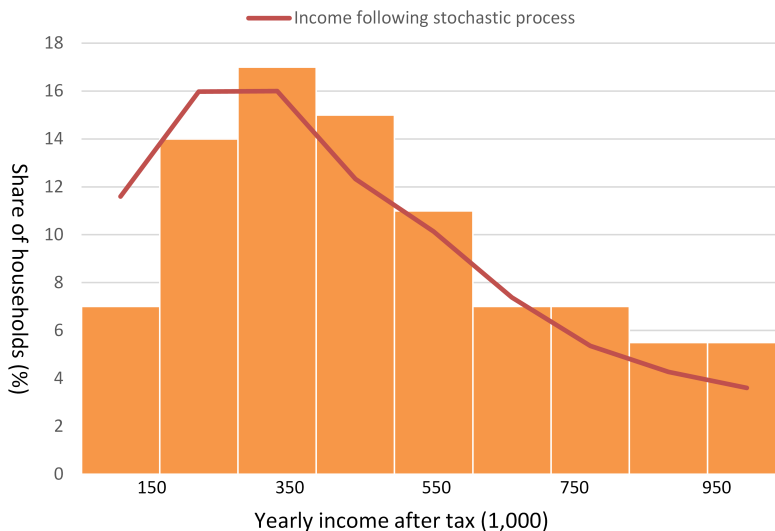


Figure 5.2.2: Income distribution in data and following stochastic process

Income is updated every 12 time periods, as the parameters for variance in the innovation of lifetime and transitory income are estimated on yearly data. In each time period, a household has a probability of becoming unemployed, so that the proportion of unemployed in the model matches observed figures in Oslo. Unemployed households receive benefits equalling the income of the first income decile in the model. Households stay unemployed for a year and then receive the income they had before the unemployment period.

5.2.3 Wealth and Savings

While data on income distribution and development has been extensively recorded by Statistics Norway historically, statistics on wealth of the population is less available. Due to the high ownership rate in Norway, a substantial proportion of household wealth is tied up in the housing market. Although the tax values of dwellings are recorded, these do not correspond to the market value. In 2009 a new valuation method was

employed by tax authorities where the tax value of a dwelling is set to 25 % of estimated market value. However, up until this date, the tax value of dwellings was set at construction time and adjusted annually with the same rate. It is therefore difficult to estimate the actual distribution of wealth of households needed to instantiate the ABM.

In order to construct a reasonable distribution, the Gini coefficient, a ratio used to measure the dispersion in population income and wealth, is applied (Gini, 1912). This coefficient ranges from 0 (perfect equality) to 1 (total inequality). Assuming that wealth, like income, follows a lognormal distribution, the scale parameter σ and location parameter μ need to be determined. Letting G be the Gini coefficient and v the mean wealth, the parameters of the associated lognormal distribution can be expressed as (Slottje and Raj, 2012, p.68):

$$\sigma = \sqrt{2}\phi^{-1}\left[\frac{G+1}{2}\right] \quad (5.4)$$

$$\mu = \ln v - \frac{1}{2}\sigma^2 \quad (5.5)$$

Where ϕ is the standard normal cumulative distribution. For the population of Oslo, the Gini coefficient of net wealth was estimated to lie at 0.63 (Davies et al., 2011). The recorded data concerning net wealth of the population is based on tax reports, so it does not represent the actual net wealth. Instead, the mean wealth used to instantiate the model is the sum of mean net wealth tied up in housing found from a survey by Statistics Norway ⁶ and the recorded net value of intangible assets. The resulting wealth distribution is plotted in Figure 5.2.3, illustrating that wealth is far more unevenly distributed in the population than income.

Households are instantiated with an initial liquid wealth from the distribution above, which they can use to enter the housing market. This wealth will develop through the simulation depending on household investment decisions and saving behavior. The savings behavior depends on household age and category and is based on historical savings rates recorded by Statistics Norway, given in Table 5.2.2. Norwegian households tend to save the lowest proportion of their income when they are approximately mid life (35-44 years), with savings peaking in the beginning and towards end of the life

⁶See "Levekårsundersøkelsen, 2007", Statistics Norway

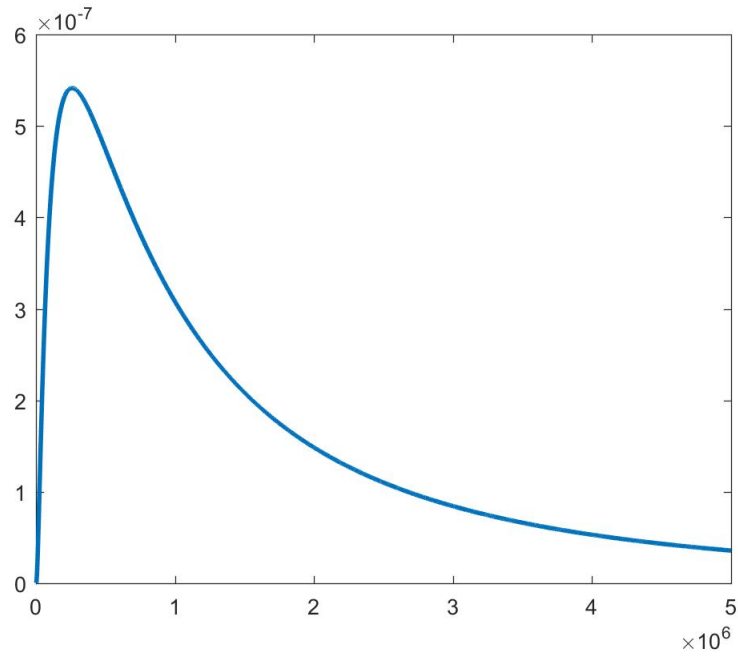


Figure 5.2.3: Lognormal wealth distribution

cycle.⁷ Young households in the model, which are instantiated with low initial wealth and income often need to save for several years before being able to buy a dwelling.

Table 5.2.2: Savings rate by age interval (Halvorsen, 2011)

Age	Savings rate
18-24	0.07
25-34	0.10
35-44	0.07
45-54	0.09
55-64	0.13
65-74	0.12
75+	0.14

5.2.4 Household Preferences

Households wish to spend a certain amount of their income on housing. This amount depends on factors such as absolute income, age and household composition. In Figure

⁷Based on data from https://www.ssb.no/a/publikasjoner/pdf/oa_201103/halvorsen.pdf

5.2.4, historical share of income spent on housing is plotted against income decile. This includes both rental costs for households who rent and mortgage costs for those who own a dwelling. From the figure, it is clear that the proportion decreases significantly when income increases. While the first income decile of households allocate nearly 30% of their consumption budget on housing, the tenth decile spend less than 15%. The expenditure across income deciles is found to only change slightly over the course of the simulation period and is therefore assumed to be constant.

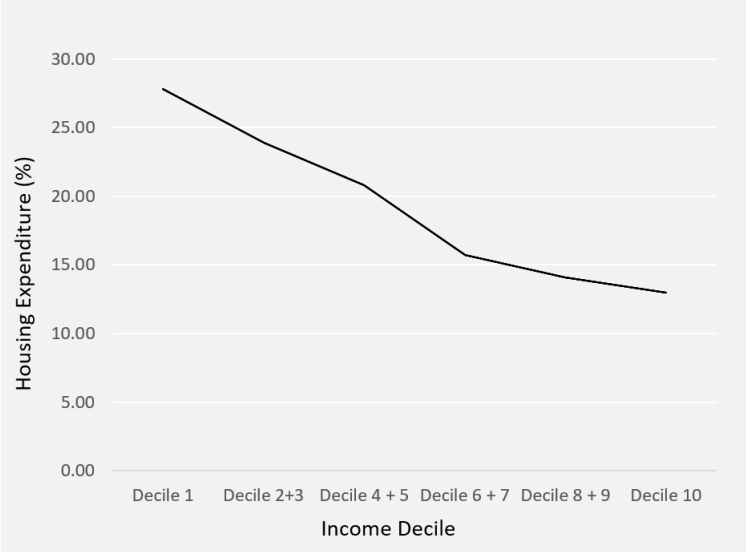


Figure 5.2.4: Share of income spent on housing by income decile ⁸

After a proportion of income is allocated to savings, a household allocates the remains between housing services and other consumption goods. While the income decile of a household determines the preferred proportion of income spent on housing, each household’s utility function depends on their preferences for certain housing attributes. In the model, there are only two attributes, namely distance to city centre (d) and housing category (c). The utility function, inspired by Palmquist (1984), can then be expressed

$$U = U(d, c, v) \tag{5.6}$$

Where v is the vector of characteristics of a household (age and category) determining the utility it attains for the two housing attributes. For each household, the utility function is maximized subject to the following budget constraint

$$y = x + P(d, c) \tag{5.7}$$

Here y is household income, $P(d, c)$ is price of the house with distance to centre, d and housing category c , while x is the amount allocated for non-housing consumption. Since it is assumed that the preferred housing expenditure is determined by household income decile, Equation 5.7 is well defined in the model. A household simply considers housing with user cost lower than its preferred expenditure. The utility function, on the other hand, is more challenging to express explicitly for a the households. One solution would be to gather extensive data on household characteristics and choice of dwelling and perform regression analysis to express some relationship. However, this would require detailed data sets that are not available for the purpose of this thesis. Instead, literature on the heterogeneity in household preferences for housing is applied to construct an explicit representation reflecting how households with different characteristics prefer different housing attributes.

In the ABM it is assumed that differences in household preferences stem from differences in either age or household category. In reality, two households at the same age, belonging to the same household category could have very different housing preferences. In addition, there might be other characteristics than distance to centre and housing category that define whether a certain household prefers one house over the other. Although the approach taken in this thesis is a rough approximation, it captures some of the main drivers for differences in housing preferences.

The heterogeneous preferences of households are modelled by assigning different priority lists of housing attributes for different household types. As explained in Chapter 4, there are four different housing categories; "house", "duplex", "semi-detachable" and "apartment", while distance is a continuous variable measuring distance to the city centre. Qualitative analysis indicate that the majority of households with children prefer to live in a house, while elderly planning to move have a higher preference for smaller dwellings (Ytrehus and Fyhn, 2006). Further, households without children who are not elderly, are most concerned about distance to the city centre when entering the housing market.

Based on these indications, the household preference sequencing is given in Table 5.2.3. Households without children between the ages of 20 and 60 have preference sequence $\langle d^-, c^+ \rangle$, so they attach more importance to distance to centre and prefer larger

housing (c^+) and smaller distance (d^-).

Table 5.2.3: Housing preferences

		Household Category	
		Children	No children
Age	20-60	$\langle c^+, d^- \rangle$	$\langle d^-, c^+ \rangle$
	60-80	-	$\langle c^-, d^- \rangle$

5.3 Agent Interaction Patterns

In each time period, the agents of the model interact by following internal behavioral rules. In an ABM of a housing market, there are two important interactions among agents that occur. First, households negotiate with the bank on mortgage terms when they wish to purchase a new dwelling. Second, households negotiate with each other on the market place for houses when funding is secured by the bank. The rules governing these negotiations are detailed in the following sections.

5.3.1 Mortgage Negotiation

In Norway, it is common for households to negotiate with several banks when considering to buy a new dwelling. Based on the household's financial history and outlook, the banks will offer to issue the household an amount of credit, specifying terms and conditions on how the mortgage will be repaid. A "proof of financing" is then provided by the bank, which the household can use as security when purchasing a dwelling. While this proof states the maximum amount the bank is willing to issue, the household may utilize only parts of the amount. The final mortgage is issued after the actual purchase and must be lower than the amount stated in the proof of financing document.

Historically, Norwegian borrowers have mainly opted for adjustable-rate mortgages, where the interest rate follows the market.⁹ Another trend is a significant proportion of issued mortgages including a repayment-free period, where the installments for the first years only consists of interest. This mortgage type is especially issued to young households who have low initial income, but high prospects for growth. When issuing

⁹To see the distribution of different mortgages see <http://www.finanstilsynet.no/no/Bank-ogfinans/Banker/Tilsyn-og-overvakning/Analyser>

mortgages with an interest-only period it is common to demand a lower LTV on the purchased dwelling.

In the ABM of this thesis, only adjustable-rate mortgages are issued, with exogenous interest rate. If a household, h decides to enter the housing market, it determines the amount it wishes to spend on housing per period, denoted $\alpha_{h,t}$ based on its current income decile (see Section 5.2.3). $\alpha_{h,t}$ is the proportion of a household's consumption budget spent on housing services. It does therefore not include downpayments, which are regarded as savings. Hence, the initial mortgage application of household h in time period t , denoted $M_{h,t}$, becomes:

$$M_{h,t} = \frac{\alpha_{h,t} * (I_{h,t} - I_{h,t} * s_{h,t})}{r_t} \quad (5.8)$$

Here $s_{h,t}$ is the savings rate of the household in the relevant time period. $M_{h,t}$ is submitted to the bank, which considers the household's income, $I_{h,t}$, and debt, $D_{h,t}$ in period t when determining the amount it is willing to lend out. The bank's lending policy is based on the historical behavior of Norwegian banks over the simulation period. This is achieved by letting the bank offer mortgages so that the average DTI in the simulation lies within the historical average.¹⁰

When the bank receives the mortgage application at $M_{h,t}$, from a household with income $I_{h,t}$ and debt $D_{h,t}$ it uses the following rules to process the application:

1. If $M_{h,t} > DTI_{max}$, reduce value of application to DTI_{max} .
2. Offer an interest-only period with probability based the historical proportion of such mortgages.
3. Calculate the term payments of an annuity mortgage with principle $M_{h,t}$, term time 25 years and interest rate r_t (the exogenous monthly interest rate in period t).
4. Check whether the household can afford an interest rate increase of δ_r . If not, set $M_{h,t}$ to be the maximum mortgage so that an interest increase is affordable.

The consumption budget estimated by the National Institute of Consumer Research

¹⁰In this thesis, the Norwegian convention, where DTI refers to total household debt divided by yearly household income, is applied. This ratio also commonly refers to monthly debt payments divided by gross monthly income in other countries.

(SIFO) is applied to determine the cost of regular consumption in step 4.¹¹ DTI_{max} is set to 5 and δ_r is set to 4% based on historically issued mortgages. The value of the term payments, $L_{h,t}$ are found using the formula for annuity loans:

$$L_{h,t} = \frac{M_{h,t} * r_t}{1 - (1 + r_t)^{-n}} \quad (5.9)$$

5.3.2 The Housing Market

Based on the offer from the bank, households turn to the housing market and consider houses they can afford with their current savings and issued credit.

Listing Houses on the Market

In any time period, a household owning the dwelling it lives in, can decide to list it on the housing market for one of two reasons:

1. If the monthly mortgage cost exceeds the minimum consumption budget, the household will want to downgrade their dwelling to one that is affordable.
2. There is a fixed probability (p_a^M), associated with the household age, that a household will want to move in a any time period.

The probability of moving is based on the historical migration within Norwegian municipalities and given in Figure 5.3.1. As these are yearly estimates, they are converted to monthly probabilities in the model. It is clear that households are more likely to move when they are younger.

If a household decides to list its dwelling on the market, it sets an initial price, $P_{d,t}$ based on the final sales prices, \tilde{P}_d of the set of dwellings with similar location and housing category ($N_{l,c}$) as their own, sold in the last three months, according to the following formula:

$$P_{d,t} = \frac{1}{|N_{l,c}|} \sum_{k \in N_{l,c}} \tilde{P}_d \quad (5.10)$$

¹¹In 2006, this amount was at 227 360 for a family of four with two young children. See <http://www.sifo.no/page/Lenker//10242/67346.html> for the yearly reports.

Table 5.3.1: Probability of moving

Age	P_{age}^M
20-29	0.19
30-39	0.12
40-49	0.06
50-59	0.04
60-69	0.03
70-79	0.03

If the dwelling is not sold after three time periods, the household will decrease the posted price with 1% in each time period it is not sold. In this way, heterogeneous supply of housing, time on market and sales prices are connected.

House Auctioning

In the Norwegian housing market, an auction mechanism is normally applied to reach market clearing. First, the seller, with assistance from an appraiser, lists its house on the market with a valuation based on recent sales of similar dwellings. Interested buyers then submit bids sequentially, in an ascending manner. When no new bids are made, the seller can choose to accept or decline the highest standing bid. If the seller accepts, the highest standing bid is paid in full by the responsible bidder. As the initial valuation is not equivalent to a reserve price (minimum) held by the seller, the highest standing bid might be lower than this value when the auction ends. While nearly all dwellings are sold through auctions in Norway, it is far more common to employ fixed prices or negotiations in other European countries.

In auction theory, the four standard auction designs are *English auction*, *Dutch auction*, the *first price sealed bid auction* and *second price sealed bid auction*. A detailed analysis of these auction mechanisms is given by for instance Menezes and Monteiro (2005). An English auction is the traditional ascending bid auction where the bidders sequentially submit their bids until no new bids are given, while the Dutch auction is a descending bid auction where the auctioneer reduces the price until one of the bidders accept. In both of these cases, some information about the valuation held by the bidders is revealed during the auctioning process. This differs from sealed bid auctions, where bids are submitted without any knowledge of the other bidders reserve prices. In a first price auction, the bidder with the highest bid pays a price equalling this bid, while this bidder pays the second highest bid in second price auction.

The bidders' valuations of the item being sold in an auction can be modelled in several ways. Two common representations are the *private value model*, where the valuation held by a bidder is a function of his type, and the *common value model*, where all bidders have the same unknown valuation. The valuation can be independent or correlated among bidders, which will affect the optimal bidding strategies and expected revenues from an auction. Another important attribute of bidders in an auction is their attitude towards risk. While risk neutral bidders only seek to maximize expected payoff, bidders who are risk averse value reduced uncertainty in their payoff.

Housing market transactions in Norway are best described as English auctions where the valuation of bidders is correlated in some way. A value model where bidders' values are correlated is often referred to as an *affiliated value model*. While different households have different valuations of a certain dwelling, their valuations are associated since it is possible to resale a dwelling after it has been acquired. This stems from the fact that housing is both an investment and a consumption good. As an investment good, assuming that households have the same risk profiles, all households should have a common value on a dwelling. However, as a consumption good, the value of a dwelling is more independent and varies based on household preferences.

In the ABM, it is assumed that bidders are risk neutral and have private independent valuations of each dwelling. This assumption leads to a dominant bidding strategy for the households, which significantly simplifies the modelling. In order to capture the fact that an affiliated value model is more realistic, the distribution of the private values is assumed to lie around the initial listing price of the dwelling. Since this price is based on recent sales of similar dwellings, it should be a good image of the valuation of others for the dwelling in question. A uniform distribution ranging in an interval around the initial listing price is applied to model the valuations of households. Letting $v_{h,d,t}$ denote the valuation held by household h of dwelling d in period t and b^{dist} the width of the distribution of valuations:

$$v_{h,d,t} \sim \mathcal{U}((1 - b^{dist})P_{d,t}, (1 + b^{dist})P_{d,t}) \quad (5.11)$$

b^{dist} is set to 5% based on reports that the dwellings on average were sold at a premium to listing price of 5.4% in 2012 and 3.7% in 2013.¹² This is a rough assumption and an

¹²Reported in <http://www.abcnyheter.no/penger/okonomi/2013/09/13/181999/>

accurate parameter value should ideally be estimated from historical data on sales to listing prices. However, this data was not available for the purpose of this thesis.

The *Revenue Equivalence Theorem* states that the four auction types presented earlier generate the same expected revenue when bidders are risk neutral and have independent private valuations (Menezes and Monteiro, 2005). Therefore, a second price sealed bid auction mechanism is applied in the ABM instead of simulating an English auction for each house transaction. This simplifies the simulation substantially as only one bidding round per sale is necessary. The dominant strategy for a bidder with valuation v^* for an object being auctioned in a second price sealed bid auction is to submit v^* as the sealed bid. Since the winner of the auction pays the second highest bid, bidding any higher than v^* would only result in additional wins when the second highest bid is above v^* , yielding negative profit. Bidding lower than v^* results in lost bidding rounds when positive profit could have been made. It can be shown that when bidder valuations follow a uniform distribution ranging from L to U , the expected profit, π , from the auction is

$$E[\pi] = \frac{n-1}{n+1} * (U - L) + L \quad (5.12)$$

Based on this relation, the expected revenue to the seller in an auction decreases with the number of bidders participating. In the ABM, employing an auction format for the market clearing process creates a connection between number of households interested in a dwelling and the final sales price of the dwelling. In each time period, after new dwellings have been listed on the market according to the rules previously explained, each household without a current dwelling performs the following actions:

1. Select N^{search} of the most expensive dwellings on the market with listing price below household budget. These are the dwellings the household can enter a bidding round for in this period.
2. Rank the selected houses according to the preference rules given in Section 5.2
3. Place a bid on the highest ranked dwelling, drawing a value from the distribution given in Equation 5.11.
4. If bidding round is lost, remove dwelling from ranked list and return to 3.

faerre-budkriger-topprisene-stuper

In each time period, a household can potentially lose N^{search} bidding rounds and stand without a new home at the end of the period. The household will then seek to enter the rental market described in the following.

Rental Market

In Norway, there are many economic advantages to owning rather than renting a dwelling. Not only is debt subsidized by the government through tax deduction, the tax on wealth invested in the housing market is relatively low. As a result, the proportion of Norwegian households owning the dwelling they live in is high compared to other countries in Europe, reaching 84% in 2015.¹³ In Oslo, this number is lower which might stem from the high proportion of young households with low savings or a short time perspective. As there are high transaction costs associated with buying and selling in the housing market, households planning to move in the near future might choose to rent instead of buy even though they have sufficient equity. In a survey performed by Statistics Norway, 98% of individuals between ages 30 and 50 report that they prefer to own rather than rent (Løwe, 2002). The proportion is slightly lower for those between 20 and 30 (93%), while it is lowest for the elderly aged between 70 and 80 (81%).

In the ABM, all households are assumed to want to enter the housing market and only turn to the rental market if there are no available dwellings within their budget. The dwellings on the rental market are provided by households who own investment houses. The rent of a dwelling in a certain time period ($R_{d,t}$), is determined by sales prices of similar dwellings and the mortgage interest rate:

$$R_{d,t} = \frac{1}{|N_{l,c}|} \sum_{k \in N_{l,c}} \tilde{P}_k * r_t \quad (5.13)$$

The rent of dwellings in the model is therefore a function of the housing price and mortgage costs associated with owning similar dwellings.

Investment Houses

In the ABM, the first dwelling acquired by a household automatically becomes the

¹³See survey by Statistics Norway on living patterns at <https://www.ssb.no/bygg-bolig-og-eiendom/statistikker/bo/hvert-3-aar/2015-11-25>

household home. However, additional dwellings can be acquired as investment objects if the household has sufficient liquid assets. The decision on whether to acquire an investment house is based on the expected first year yield on the dwelling $E[Yield_{d,t}]$:

$$E[Yield_{d,t}] = \frac{Rent + E[Appreciation] + TaxSavings - Interest}{(1 - LTV) * P_{d,t}} \quad (5.14)$$

The rent is the rent received in the next year if the dwelling was rented out to the price in Equation 5.13. $E[Appreciation]$ is the expected appreciation on the dwelling in the next year estimated by extrapolating the average house price appreciation in the last year. The interest payments are calculated based on the mortgage necessary to cover the listing price of the mortgage. Similarly, the LTV is the loan-to-value associated with the purchase. $(1 - LTV) * P_{d,t}$ is therefore the downpayment made by the household if the dwelling is purchased.

According to Brueggeman and Fisher (2008)[p.307], the expected return and risk of real estate investments typically lies between that of bonds and stocks. However, in Norway, the risk (often measured by the standard deviation of returns) attached to housing investments has historically been more similar to bonds than stocks. In the model, the risk free deposit rate ($r^{deposit}$) is marked up by a constant (r^{invest}) to determine whether a household invests in a house or not. The household submits a bid for the dwelling if the expected yield exceeds the required return:

$$E[Yield_{d,t}] \geq r^{invest} + r^{deposit} \quad (5.15)$$

r^{invest} is set to 5% in the simulation, giving a required return lying somewhere below the mean return on stocks. Since there is no guarantee that the dwelling will be rented out in the first month, and the final selling price of the dwelling might lie above its listing price, $E[Yield_{d,t}]$ is not necessarily equal to realized yield even if the appreciation on the dwelling is as expected. After an investment house is purchased, it is listed on the rental market with rent determined as in Equation 5.13.

5.4 Model Execution

In each time period, all households follow the behavioral rules specified in the previous sections. Agents act on a monthly basis in the simulation, giving twelve time periods per year where households follow their behavioral rules. The model is instantiated in the year of 2006, so there are a total of nearly ten years of simulation to reach the current date. In Figure 6.2.1, a flowchart of this process for one household is shown. The flowchart indicates that each household acts sequentially, while in reality households are acting simultaneously. Therefore, in the implementation, instead of completing a full round of actions for each household, each step in the flowchart is performed by all households before any household moves on to the next step. All households will therefore have updated their income before any household applies for a mortgage.

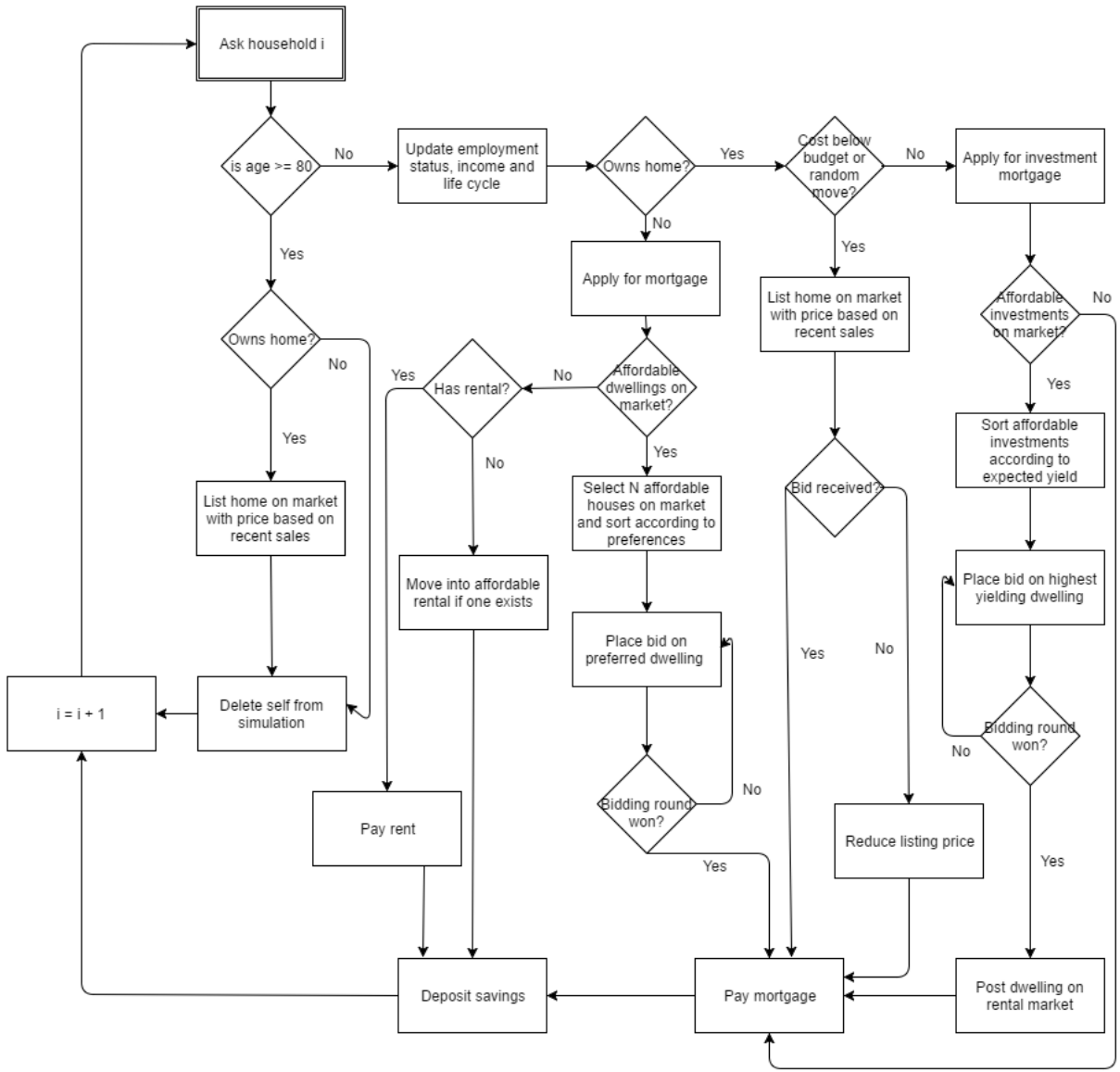


Figure 5.4.1: Flowchart of household behavior

Chapter 6

Implementation

In this chapter, the implementation of the ABM presented in Chapter 5 is discussed. In Section 6.1, a brief overview of available ABM software is given and the software applied in this thesis is introduced. Further, in Section 6.2, a description of the file organization of the implementation is presented.

6.1 Choice of ABM Software

There exist numerous different platforms for developing ABMs. While some are tailored for certain research areas, others offer flexible solutions that can be applied for any type of model. One alternative when implementing an ABM is to program the model from scratch in an object oriented programming language like C++. While this offers the highest degree of flexibility and might lead to shorter running times, it requires the implementation of many features that can be found readily available in platforms developed for ABM purposes. Other alternatives include Java based toolkits such as JABM and AMP.¹ As an ABM is defined by a set of rules for interaction between agents and transitions between different states, the resulting macro output should be independent of software choice.

In this thesis, the ABM software NetLogo is chosen for implementation.² NetLogo is

¹See <http://jabm.sourceforge.net/> and <http://www.eclipse.org/amp/> for an introduction to these toolkits

²Software documentation can be found at <https://ccl.northwestern.edu/netlogo/>

based on the programming language Logo and is free and open source. Of the published literature involving ABMs, NetLogo has been applied in numerous instances. Examples include Feitosa et al. (2011), implementing a simulator for urban segregation, and Lee et al. (2014) analysing policies for energy reduction. An important factor determining the choice of software is NetLogo’s capabilities of incorporating spatial data in the modelling. The NetLogo GIS-extension enables geographical data to be read so that the agent ”world” has a spatial dimension.

6.2 File Organization

While the ABM is implemented in NetLogo, MATLAB is applied for data preprocessing due to its efficient matrix computations. The initial households and dwellings are created by a MATLAB script and loaded to separate Excel files. The NetLogo model reads two types of data files, one with attributes for the initial households and dwellings and one with the households and dwellings entering the model during the simulation due to net immigration and constructed houses. The NetLogo script is structured in one file, but run as two separate files. The *setup* script instantiates the agent world with a set of households and houses, loading the GIS shapefile to place the houses on a geographic location. The *run* script is executed one time for each period and contains the agent rules for interaction and updating. In each time period, the relevant exogenous variables are updated and each individual agent state preserved for the next iteration. The macro phenomena resulting from the agent interactions are finally loaded to an Excel result file. In Figure 6.2.1 an overview of the file organization and flow between files is shown.

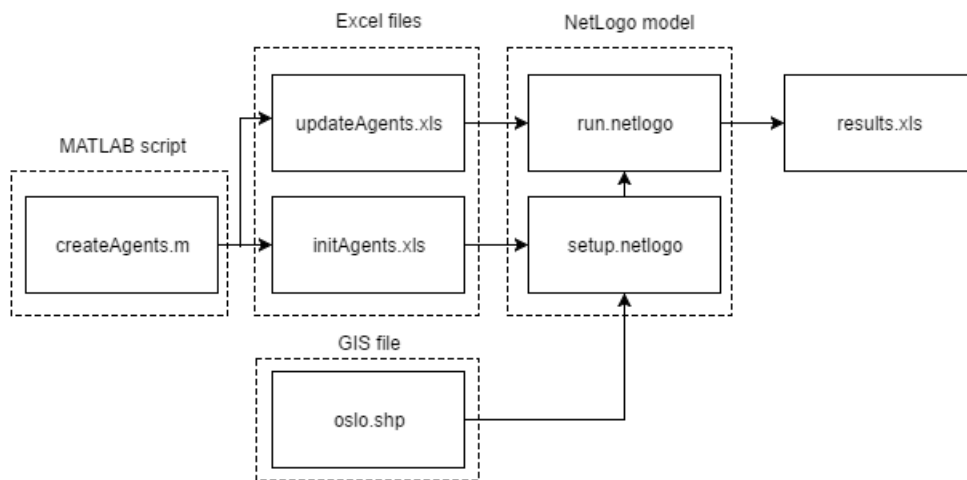


Figure 6.2.1: Flow between files in implementation

Chapter 7

Simulations

In this chapter, the specified ABM is applied to perform numerous simulations. In Section 7.1, the model is instantiated to match conditions in Oslo in 2006 and run with appropriate parameters for a simulation period of ten years. The development of variables that are endogenous to the model are checked against their empirical values, in order to ensure that the model generates reasonable results. Subsequently, in Section 7.2, the ABM is applied to evaluate the effect of housing policy modifications and exogenous shocks.

7.1 Model Evaluation

In Chapter 5, the micro behavior and characteristics of households acting on the housing market are explicitly defined, making it possible to construct representative agents in a computer program. While some variables like interest rate and unemployment are set exogenous to the simulation, the development of for instance housing prices and home-ownership rates are the result of thousands of actions made by these agents. By comparing the macro evolution of the endogenous variables to the historical development, it is possible to evaluate whether the defined micro rules for agent interactions are plausible. If the model can be validated in this respect, it is possible to perform projections and counterfactual experiments, giving an indication of how the market would have developed if housing policies had been modified.

Housing Prices

One of the most important variables in the simulation is the housing price development. In Figure 7.1.1, the average square meter price in the model is plotted against historical prices. Short term price development may be sensitive to variations in the specific dwellings sold in a time period and the simple moving average is therefore shown.¹ The model is able to predict both the overall shape and magnitude of housing price development over the simulation period. However, the empirical downturn in prices during the financial crisis is not completely captured by the model. In the simulation, prices instead level off in these time periods, before sharply increasing in the following years. In the model, the gradually increasing interest rate leads to a significant decrease in the magnitude of the mortgages issued by the bank in the early years of the simulation. The observed rise and fall historically may indicate that banks in reality were less strict on checking whether a household could afford an interest increase before issuing a mortgage, than the bank in the model.

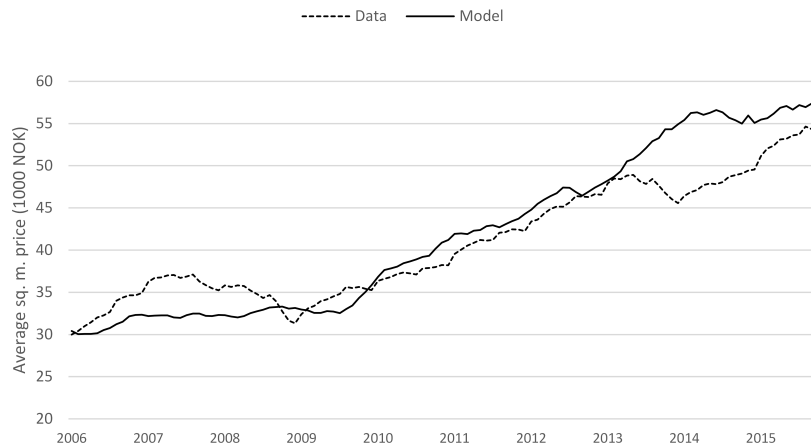


Figure 7.1.1: Price development of model and historical data

The model also fails to predict the stagnation in prices towards the end of 2013. There is no development in fundamental factors explaining why prices did not continue to grow in this period, which might indicate that household expectations was an important factor. As the ABM does not include expectations as a variable, this would explain why it is not able to predict the stagnation. However, the final price reached towards the end of 2015, approaches the recorded figure.

¹The simple moving average is taken as the unweighted mean of the price in the time period and immediate previous and subsequent time periods.

Drivers leading to the observed price development include high immigration compared to building activity, decreasing interest rates and liberal lending policy by the bank. Further, wealth is unevenly distributed in the population with a small proportion holding the majority of wealth. With overall high appreciation on housing and several tax benefits of investing in the housing market, the wealthy households have had incentives to enter the market to buy a second and third dwelling. These additional buyers on the market have contributed to increase demand further and driven prices higher.

Due to the micro-level nature of the ABM, it is simple to analyse price development for different geographical areas and housing characteristics. In the model, there are four different housing categories ranging from "house" to "apartment". While apartments often are located near the city centre and are small in size, houses can mainly be found in districts towards the city border. In Figure 7.1.2, the average square meter price of sold dwellings by housing category is shown. In the model, the price of apartments has had a significantly steeper growth than the other categories. This is to be expected as net immigration mainly consists of young households with low income and savings. Further, apartments are an easier target for investors as they are generally cheaper than larger dwellings. This surplus demand leads to bidding rounds with many potential buyers resulting in a higher sales price.

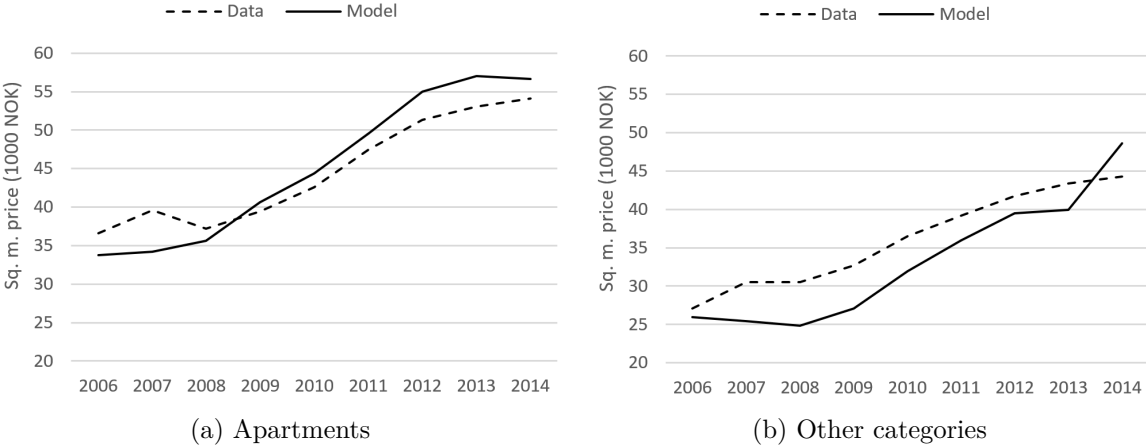


Figure 7.1.2: Price development of dwellings by housing category

It is also interesting to analyse how prices develop in the different geographical districts in the model. As the model is spatial, all dwellings in the market have a location in a 2-dimensional grid representing the city. By letting darker colors represent higher prices, a plot of the dwellings before and after the simulation can be applied to visualize the

price changes in the different areas. This is shown in Figure 7.1.3, for the initial and final periods of the simulation. Central districts are clearly more densely populated than suburban areas. Although the figures indicate that house prices have increased in all districts, it is clear that the prices in districts closer to the city centre have had a higher price growth than less central areas. One explanation to this observation is that apartments mainly are located near the centre and that it is the demand for this housing category rather than location that drives the prices. Alternatively, an important driver may be derived from the household's preference functions. The model has a high inflow of young households who prefer to live centrally. This contributes to increase the demand for central dwellings, driving up prices.

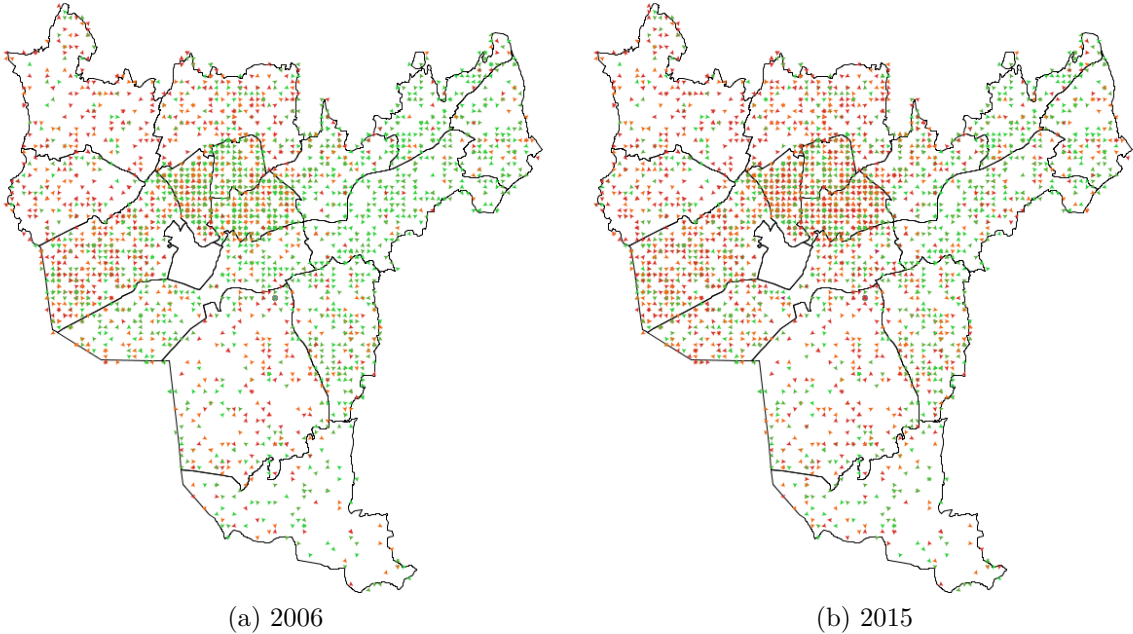


Figure 7.1.3: Geographical price development

Household Debt and Savings

In parallel with the increase in housing prices, household debt has grown significantly in Oslo over the simulation period. Debt and housing prices have empirically been observed to reinforce each other. While higher debt make dwellings more affordable to households, higher prices make larger mortgages necessary.² In Figure 7.1.4a, the average household mortgage debt in the model is plotted against historical averages. As Statistics Norway only performs this survey every three years, only a few data points are available for the simulation period. However, debt of households in the model seem to follow the same growth as the historical data.

Average household savings is shown in Figure 7.1.4b, with a development similar to the data. In the model, this is the amount saved by households that is not invested in housing. Therefore, the data used for comparison is the historical mean household savings held as bank deposits, bonds, stocks and other negotiable assets.³ The total savings rates of households in the model are based on empirical household behavior, however the proportion allocated to housing versus other investments is based on the less empirically grounded household investment rules. With the reasonable development of savings and debt in the model, the confidence in the rules and parameters governing investment behavior can be enforced.

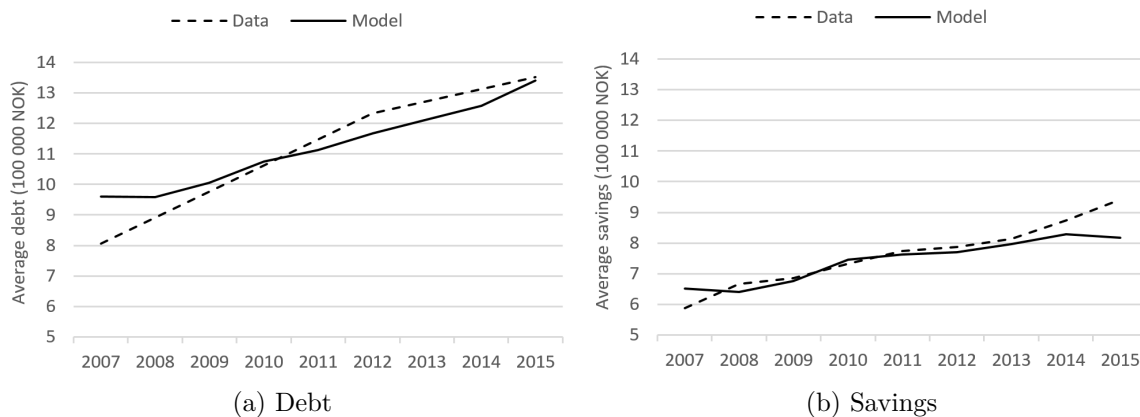


Figure 7.1.4: Average debt and savings of households

²See for instance Anundsen and Jansen (2013) on the self-reinforcing effects between housing prices and credit.

³See "Levekårsundersøkelsen" at <https://www.ssb.no/bygg-bolig-og-eiendom/statistikker/bo/hvert-3-aar/2015-11-25>

DTI of Issued Mortgages

While there is no hard DTI-limit enforced by the government on mortgages issued to Norwegian households, the proportion of mortgages with DTI exceeding five has been negligible in the last decade. In the simulation, the limit is therefore set to five and it is hoped that the rules outlined in Section 5.3.1 lead to a realistic lending policy. In Figure 7.1.5, the resulting average DTI of households in the model under 35 years is shown.

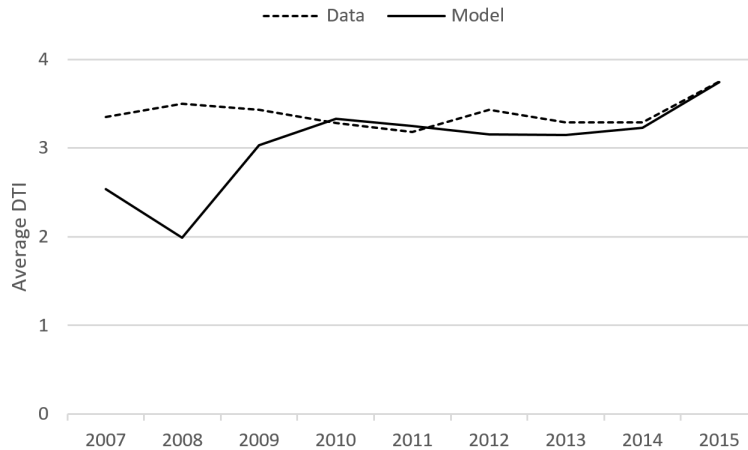


Figure 7.1.5: Average DTI of mortgages issued to young households

In the model, the DTI is lower than the data in the years leading up to the financial crisis. This may be an indication that the actual practices of banks differed from the practice in the model in these years. In 2008, the interest rate was at its peak due to the world wide financial turmoil. In the lending policy of the bank in the model, mortgage applications are only accepted if the household can afford an interest increase of 4%. During the period of high interest rate, many of the initial mortgage applications are therefore rejected. In reality, banks may have eased this restriction leading to the high observed DTI of loans also in this period. This might also explain why predicted prices in the model were below the data in the initial years of the simulation.

The Rental Market

In Norway, the home-ownership rate has historically been high compared to other European countries. The numerous tax benefits of owning property together with a culture for home-ownership are some of the factors leading to this development. The rental market in the ABM consists of dwellings bought by household investors who own mul-

tiple dwellings. The rent of the dwellings in this market is a direct function of the prices on the freehold market and the interest rate, as explained in Section 5.3.2. While analysis of the rental market is not the main purpose of this thesis, it is interesting to study how the proportion of households living in freeholds and rentals develops over the simulation period. In Figure 7.1.6, the home-ownership rate in the model is plotted.

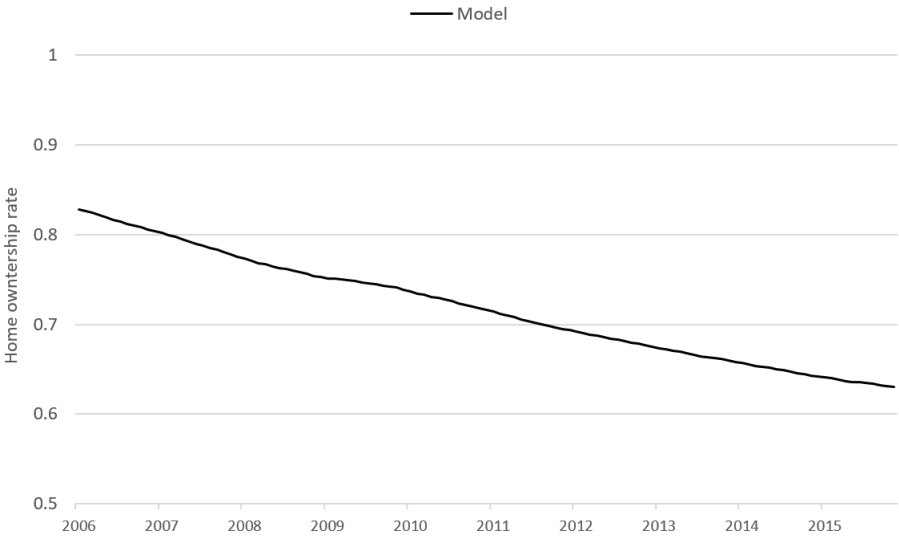


Figure 7.1.6: Proportion of households owning their home

As seen from the plot, less than 65% of households in the model live in freeholds at the end of the simulation period. While data on the home-ownership rate of the Oslo population is not readily available, Statistics Norway report that around 76% of Norwegian households owned a dwelling in 2015.⁴ However, this is the aggregated proportion for the entire country and not specific for the Oslo population. The housing investment activity in metropolitan areas is significantly higher than in less populated areas⁵, leading to a higher proportion of investment owned dwellings. Further, the steady inflow of young households with low equity and income leads to a higher demand for rentals. Based on these factors, it is reasonable to believe that the home-ownership rate in Oslo in reality is lower than the countrywide reported figure.

Sales-to-List Ratio

⁴As reported by Statistics Norway in <https://www.ssb.no/bygg-bolig-og-eiendom/statistikker/bo/hvert-3-aar/2015-11-25>

⁵For instance discussed in https://www.nrk.no/norge/_hytter_-i-storbyene-presser-opp-boligmarkedet-1.12284786

There are two mechanisms driving the development of house prices in the model. First, when a dwelling is put on the market, its listing price is based on recent sales of similar dwellings. This price is also reduced gradually if the dwelling is not sold in a certain amount of periods. Second, sales are completed through bidding rounds, where households base their valuation of the dwelling on a draw from a distribution around the listing price. The resulting sales price therefore depends on the number of bidders, or the demand for that certain dwelling. In Figure 7.1.7, the mean sales-to-list ratio of sales over the simulation period is shown.

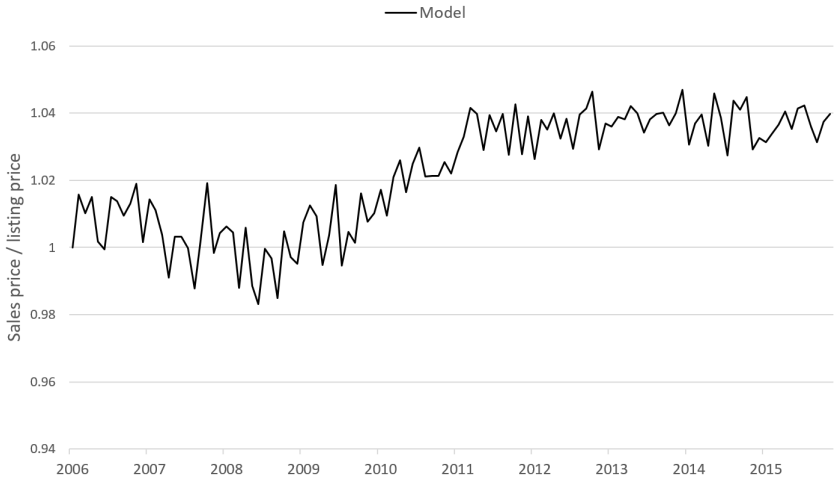


Figure 7.1.7: Average sales to listing price

During the financial crisis, there is a clear dip in this ratio, where dwellings on average are sold at a price slightly below the listing price. The number of dwellings on the market is high in this period as few households can afford large mortgages due to the high interest rate. In 2009, the interest rate was significantly reduced and the demand for dwellings therefore increased. This is reflected in the rise of the sales-to-list ratio. The ratio stabilizes at around 1.04 towards the end of the simulation period, leading to the observed price increase discussed earlier. Empirical data on the result of bidding rounds in Oslo was not available for the purpose of this thesis. It is therefore difficult to determine whether the development shown above is reasonable. For future work on the topic of housing markets and ABMs, detailed data on housing transactions could be applied both to calibrate and validate the model.

7.2 Counterfactual Experiments

Having evaluated the ABM and established that it yields reasonable output, experiments where updates to government policies affecting the market can be performed. Housing policies encompass a wide range of different instruments including taxation, rent policies and regulation on lending. In Norway, housing policies have undergone significant changes in the last decades. During the 1980s, credit markets were liberalized and government subsidies and interventions in the market reduced to a minimum.⁶ However, due to the rapid rise in housing prices, increased attention has been directed to whether government intervention is necessary. Updates to the guidelines on how banks process mortgage applications have been enforced and property tax introduced. In the following sections, counterfactual experiments are performed in order to analyse the effect on endogenous variables. Three policy modifications are chosen for analysis. In Section 7.2.1, an experiment where government guidelines regarding LTV and DTI-limits are tightened is performed. Further, in Section 7.2.2, the effect of removing the interest deduction on housing prices is evaluated. Finally, an interest shock is imposed on the model in order to analyse how the market would react in case of a drastic change in one of the exogenous variables. Other experiments, for instance the enforcement of property tax, were also conducted. However, the effect on housing prices was found to be negligible and the analysis is therefore not included.

7.2.1 LTV and DTI-Limits

In 2010, the Financial Supervisory Authority of Norway enforced new guidelines on the minimum downpayment necessary for housing purchases.⁷ Up until this date, there were no restrictions on the maximum LTV-ratio, so banks simply made their own risk assessments when deciding on the amount they were willing to lend out. The new guidelines state that an issued mortgage should not exceed 90% of the market value of the dwelling being purchased. However, additional assets posed as collateral for the loan, for instance dwellings of family members, could lead to exemption from this

⁶A thorough analysis of Norwegian housing policies during the last 40 years can be found here: <https://www.hioa.no/eng/Aktuelle-saker-fra-2011/Housing-policy-in-Norway>.

⁷Full description of guidelines given in http://www.finanstilsynet.no/Global/Venstremeny/Rundskriv_vedlegg/2010/1_kvartal/Rundskriv_11_2010.pdf and http://www.finanstilsynet.no/Global/Venstremeny/Rundskriv_vedlegg/2011/4_kvartal/Rundskriv_29_2011.pdf

rule. The bank also has authority to waive the rule if there are other extraordinary circumstances leading the bank to believe the household carries low risk. An update to the guidelines was made in 2011, when the maximum LTV-ratio was reduced to 85%.

The new guidelines have been criticized for increasing the gap in living standard between first-time buyers with wealthy backgrounds and those with less financial support. The majority of mortgages exceeding the LTV-maximum before the new guidelines were enforced, were young households with low savings. After the new downpayment requirement, households with low savings and without relatives assisting with collateral are excluded from the market. Despite the new guidelines, nearly 28% of issued mortgages for house purchase exceeded the 85% maximum in 2015. This indicates that a substantial proportion of mortgage-applicants are backed by alternative collateral.

In Figure 7.2.1, the average square meter price over the simulation period is shown for benchmark parameters (set to fit realistic conditions) and for the experiment where the 85% rule is strictly enforced. The latter illustrates the price development if alternative collateral and extraordinary circumstances did not allow the bank to lend out more than than the government guidelines imply.

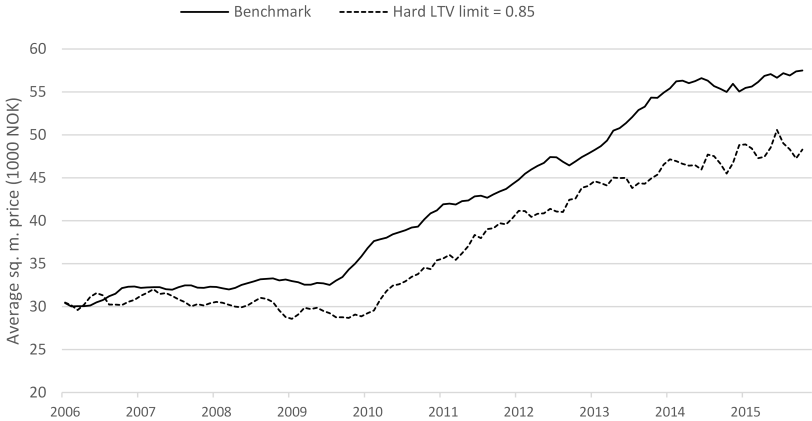


Figure 7.2.1: Price development with hard LTV-limit

While the increase in prices is slightly lower when the LTV-limit is strictly enforced, the price development has the same shape as for the benchmark case. Although there is a high proportion of issued loans exceeding the 85% rule in the benchmark simulation, many of these loans are only barely above the limit. Therefore, the demand for housing is not significantly affected by enforcing a hard limit. Other drivers such as immigration,

income growth and low interest rates contribute to maintain the substantial housing price growth.

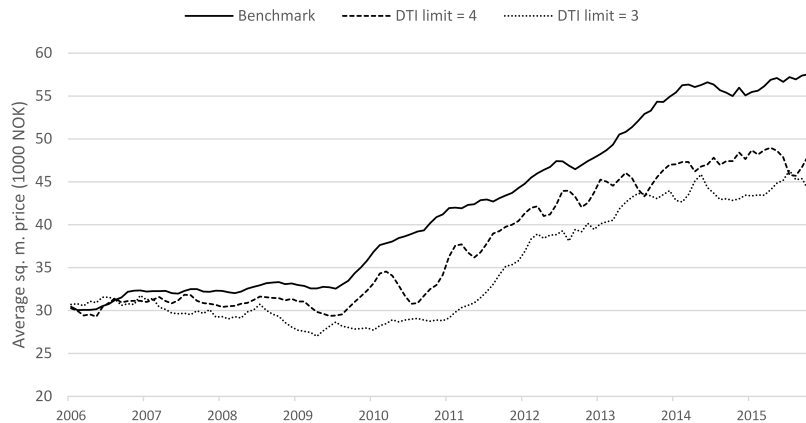


Figure 7.2.2: Price development with different DTI-limits

Another instrument that can be used by the government to restrict the amount of debt issued to households is enforcing a maximum DTI-limit. While LTV-limits indirectly reduces the debt burden of households by requiring a downpayment, setting explicit DTI-limits directly lowers the size of mortgages. In Norway, DTI refers to the total debt of a household divided by its yearly income whereas in the US, the term refers to the monthly debt payments divided by monthly income. The Norwegian interpretation is therefore independent of the interest rate, involving the absolute debt and not the debt payments. In Figure 7.2.2, the housing price is plotted for two alternative DTI-limits. Clearly, lowering the DTI-limit reduces the growth of housing prices.

7.2.2 Tax Deduction

Policies involving tax deduction of interest payments are enforced in many countries, including Norway. The rationale for this policy is symmetry between the treatment of interest income and interest expenses. As interest income is taxed, expenses should be tax deductible. However, for investments in the housing market, Norwegian regulations state that profits are non-taxable if a household has inhabited the dwelling for more

than 12 months.⁸ For investors who do not inhabit their investment dwelling, it is only fair that interest paid on debt used to finance the purchase is tax deductible as gains on a sale is taxed. However, the policy clearly favours home-owners and raises the question of whether mortgage interest payments should be tax deductible. In Norway, 28 % of interest expenses are tax deductible. Therefore, the relevant interest after taxes in time period t , r_t , is a function of the interest rate demanded by the bank (r_t^B) and the tax deduction rate:

$$r_t = (1 - 0.28) * r_t^B \tag{7.1}$$

In practice, tax deduction reduces the relevant interest rate and therefore the cost of a mortgage. As the interest rate is an important driver for housing price growth, it is expected that a removal of the tax deduction policy will lead to reduced prices. In Figure 7.2.3, the development of prices with and without the tax deduction policy is shown.

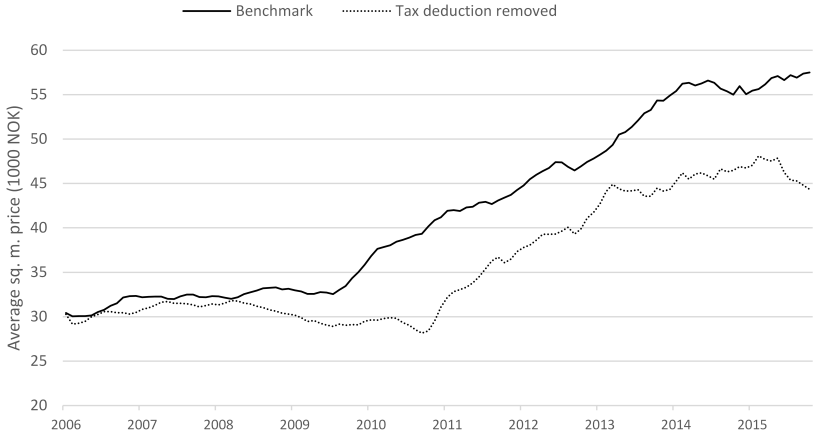


Figure 7.2.3: Price development with removal of tax deduction policy

Removal of the tax deduction policy does reduce housing prices. While the price starts to grow shortly after the peak of the financial crisis in the benchmark case, the period with no growth is prolonged when there is no tax deduction. Subsequently, the price grows significantly in both cases. However, without tax deduction, it appears to level

⁸See full description of tax regulations at <http://www.skatteetaten.no/no/Person/Selvangivelse>

off towards the end of the simulation. Over the last three years of the simulation, the benchmark price increases by nearly 20%, while the price with no tax deduction levels off.

7.2.3 Interest Rate Shock

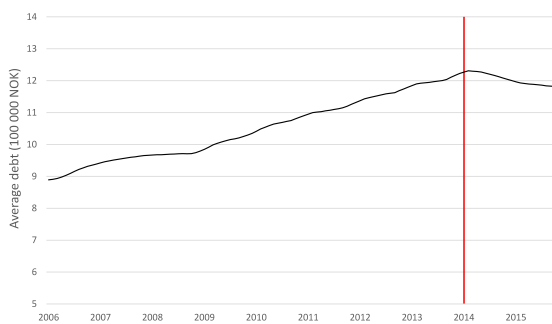
Exogenous shocks are sudden changes to the variables that are external to the model. Evaluating how endogenous variables are affected by exogenous shocks can convey insights to how the market would respond to unexpected changes in conditions. The two final years of the simulation are applied to test the model behavior under an interest shock.

The interest rate is an important variable in the simulation as it determines the cost of mortgages, but also the required return on housing investments. After the financial crisis, the interest rate on Norwegian mortgages has been decreasing, reaching its lowest value in decades towards the end of the simulation period. The bank in the model checks whether a household can afford a significant interest increase before issuing a mortgage, so it is not expected that a higher interest rate will result in many forced sales. However, a higher rate will certainly reduce the size of issued mortgages and the demand for investment houses which in turn should impact prices. In Figure 7.2.4a, the average square meter price is plotted before and after an interest rate shock of 5%. The price levels off quite quickly before decreasing by more than 10% during the last year of the simulation.

Household debt is also affected by an interest rate shock, as shown in Figure 7.2.4b. When the interest rate increases, the demand for credit is reduced leading to a stagnation in the debt growth. Jacobsen and Naug (2004b) estimate a model of household debt containing the effects of housing prices, unemployment, housing stock, house sales, interest rate, income and number of students. In their model, the isolated effect of an interest increase of 5% is at about -8%. As there are other variables in the ABM which develop after the shock, the interest effect cannot be evaluated in isolation. However, the observed reduction in debt of around 5% in the model is reassuring.



(a) Average sq. m. price



(b) Average household debt

Figure 7.2.4: Price and average debt following 5% interest shock

Chapter 8

Discussion

In this chapter, a critical discussion of the results presented in Chapter 7 is given. First, in Section 8.1, various model sensitivities are analysed in order to determine how the model responds to different assumptions. In Section 8.2, the effect of the randomness inherent in the model is assessed together with stability tests of the model output. Finally, in Section 8.3, the simulations performed are studied in light of standard economic models in order to decide whether ABMs are in fact necessary for analyses of the housing market.

8.1 Model Sensitivities

The behavioral rules of the households in the ABM are mainly based on historical data, however several parameters are difficult to estimate and have been set using rough assumptions. In order to evaluate the sensitivity of the model to the choice of these parameters, Theil's inequality coefficient is applied. This measure, suggested for ABM sensitivity analysis by Helbing (2012), is a statistical forecasting evaluator. Letting A_t denote the actual observations and P_t the corresponding predictions, the evaluation of the model, UI , is given by:

$$UI = \frac{\sqrt{\frac{1}{n} \sum_{t=1}^{t=n} (A_t - P_t)^2}}{\sqrt{\frac{1}{n} \sum_{t=1}^{t=n} A_t^2 + \frac{1}{n} \sum_{t=1}^{t=n} P_t^2}} \quad (8.1)$$

When UI is zero, there is a perfect match between the actual observations and the predictions of the model. Running the simulations for different parameter choices, Theil's inequality coefficient is calculated for the time series of the mean square meter price, debt and savings of households. It is then possible to evaluate how the predictive power of the model varies with updates to the parameters. Although there are numerous different parameters in the model, sensitivity analysis is only performed for those loosely grounded on empirical evidence. For instance, the age dependent probability of moving is estimated based on accurate data on the moving behavior of households and is therefore excluded from the analysis. Ideally, a thorough analysis of all parameters should be conducted, however this is deemed unfeasible for the time frame of this thesis.

The variables chosen for analysis are the number of dwellings a household considers for purchase in each time period, N^{search} , the markup on the deposit rate used by investors to determine whether to invest in the housing market, r^{invest} , and the width of the distribution around the listing price of dwellings determining household valuation, b^{dist} . Due to limited available data for estimating these parameters, it is important to evaluate their effect on the model. In Table 8.1.1, the results of the sensitivity analysis is shown.

Table 8.1.1: Sensitivity analysis

<i>Instance</i>	N^{search}	r^{invest}	b^{dist}	UI_{price}	UI_{debt}	$UI_{savings}$
<i>BM</i>	10	0.05	0.05	0.047	0.047	0.040
<i>I1</i>	5	0.05	0.05	0.042	0.050	0.040
<i>I2</i>	15	0.05	0.05	0.048	0.046	0.051
<i>I3</i>	10	0	0.05	0.042	0.048	0.047
<i>I4</i>	10	0.10	0.05	0.036	0.047	0.038
<i>I5</i>	10	0.05	0.03	0.071	0.051	0.035
<i>I6</i>	10	0.05	0.07	0.088	0.048	0.055

For the benchmark instance households can place bids on a maximum of 10 dwellings in each time period, their valuation of dwellings lie within 5% of the listing price and investors require a 5% markup on the deposit rate to invest. In this case, the inequality coefficient is equal for the price and debt time series and slightly lower for savings.

An important assumption for the model building in this thesis is a completely bottom-up approach. Therefore, no parameters have been calibrated by optimizing over the error of predictions. Instead, parameters are solely set to values deemed to be reasonable based on observed behavior of households. Hence, the inequality coefficients may be lower for alternative values of the parameters tested in the sensitivity analysis.

When varying the N^{search} parameter, instances with the number of dwellings set to 5 and 15 are tested. This is assumed to be an appropriate interval as it is reasonable to believe households wishing to enter the housing market will bid on at least 5 and no more than 15 dwellings before postponing their purchase to later time periods. The evaluation of the instances show that letting households bid on less dwellings than the benchmark leads to lower inequality coefficient for the price, but higher coefficient for the debt. Similarly, the predictions when increasing N^{search} do not strictly outperform the benchmark instance. This indicates that setting N^{search} to 10 was a good choice. Further, the variance of the inequality coefficient is relatively low for the different variables and instances. Therefore, it can be inferred that the model provides steady predictions across the variables and that it is not highly sensitive to the setting of N^{search} .

The r^{invest} parameter is important when households decide whether to invest in additional dwellings. As explained in Chapter 5, it is set to 5%, resulting in a total required yield lying somewhere between the deposit rate and the mean return on the stock market for the simulation period. However, the return actually required by investors is very difficult to estimate. The model is tested with r^{invest} at 0 %, leading to a the required return equalling the deposit rate, and at 10 %, for which the required return approaches the return on stocks. Again, the sensitivity tests show that the model is not very sensitive to the parameter setting. However, for instance *I4*, the inequality coefficients are lower than the benchmark for both the price and savings, while it is identical for household debt. This indicates that a markup of 5% might have been too low.

The model is tested with the b^{dist} parameter, defining the range of household valuations of dwellings on the market, at 3% and 7%. As households bid their valuations in a bidding round, this parameter determines the interval of possible bids. The sensitivity tests show that the model is a lot more sensitive to changes in this parameter than both N^{search} and r^{invest} . While a lower value for b^{dist} only allows for dwellings to be sold at a price slightly above their listing price, a higher value leads to a price growth

exceeding the historical growth. Through access to detailed micro data on transactions in the housing market, increased confidence in the value of b^{dist} could be achieved. This is left as a suggestion for further work on the topic.

8.2 Effect of Random Parameters

The results presented in Chapter 7 are the outputs of single simulation runs. As many components of the model develop through draws from some probability distribution, the model output will not be identical for repeated simulations. For instance, the initial matching of households and dwellings is governed by a random function. Similarly, household income follows a stochastic process which will certainly return different values for a specific household in each simulation. This is a common characteristic of ABMs as the micro-level behavior and characteristics of agents are difficult to model deterministically.

Despite the randomness inherent in the model, it is hoped that the emergent phenomena observed are independent of simulation "seed" and that the results in Chapter 7 are representative. In order to test this hypothesis, the benchmark model is run 30 times and the time series of the average square meter price recorded. Subsequently, the mean value is computed for each time period and plotted together with bands illustrating the maximum and minimum value of the simulations, as shown in Figure 8.2.1. The bands are narrow, indicating that the development of the average square meter price only varies slightly with each simulation. Further, the mean time series appears similar to the runs in Chapter 7, confirming that these runs were representative. The variations around the mean are naturally larger towards the end of the time series as small initial variations will propagate through the simulation.

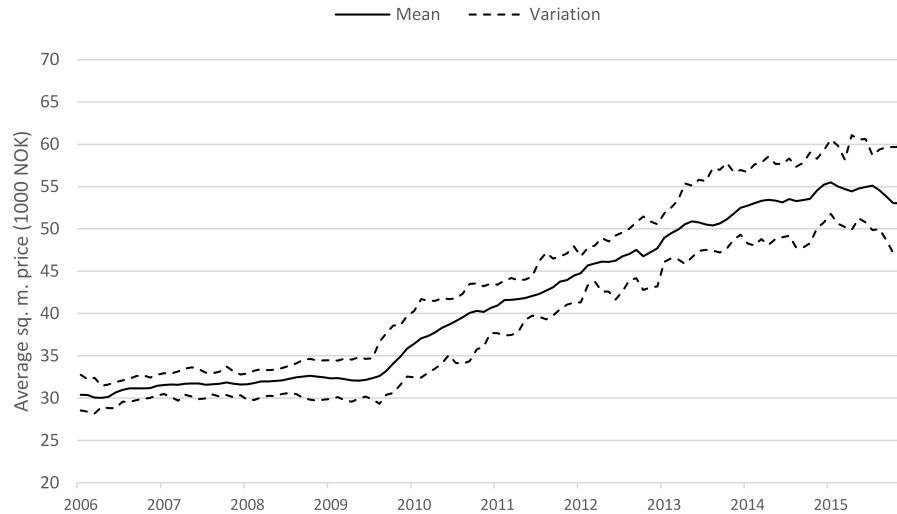


Figure 8.2.1: Output from different simulation seeds

8.3 ABMs and Standard Economic Models

An important goal of this thesis is to evaluate whether ABMs can provide new insights to the housing market. In Chapter 2, three main types of economic models commonly used to analyse the housing market are presented. In theoretical models, supply and demand functions are constructed to perform equilibrium analysis. Macroeconometric models, often built on the theoretical foundation, commonly estimate regression models of the market. Finally, DSGE models have a micro-founded approach more in line with ABMs. However, as opposed to ABMs, DSGE models make the assumption of an equilibrium which can be computed by summing over all agent actions.

The simulations performed in Chapter 7 involve both testing of model validity and what-if analyses. First, the ABM is evaluated using benchmark parameters and historical data for comparison. Next, two different types of experiments are performed. While shocks to the interest rate merely is implemented as an update to model parameters, the simulations involving DTI/LTV-limits and interest deduction are the results of modifications to agent interaction rules.

Theoretical models are unsuitable for performing any of the analyses executed in this

thesis. Due to their theoretical nature, they are seldom applied directly for market analysis. Macroeconometric models, on the other hand, are often empirically validated and used to perform forecasts. As these models frequently formulate the endogenous variable as a linear function of the exogenous variables, the interest rate shock could easily have been analysed. However, as discussed in the introduction, there is a certain danger of applying regression techniques. This is the basis for the Lucas critique, that relationships observed in historical data not necessarily indicate relationships of the future.

Moreover, macroeconometric models would in general have difficulties in estimating the effect of the policy modifications tested in this thesis. To test the effect of a stricter lending policy, one alternative would be to include the LTV/DTI limits as a variable in the model. However, this assumes that different levels of these limits have been enforced historically. Regarding the effect of interest rate deduction, experiments can easily be performed if the policy is assumed to target all agents. Then, the updated interest rate can simply be input to the model. However, when agents are to be treated differently, for instance if removal of tax deduction is not to be enforced on investors, macroeconometric models are not suitable.

DSGE models were partially developed as a response to the critique towards macroeconometric models. Hence, they offer greater flexibility and should be able to handle some of the challenges faced by these models. For instance, one of the main intentions of DSGE models is policy experiments. In fact, the analyses performed in this thesis could easily be implemented in a DSGE model. However, DSGE models commonly assume rational expectations, representative agents and perfect markets and do not incorporate the implications of imperfect information. In the ABM in this thesis, households do not have perfect information regarding the dwellings on the market. Instead, they search only for a limited number of dwellings before entering bidding rounds. While this is a natural consequence of household behavior in an ABM, it is not easily represented in a DSGE model.

Chapter 9

Conclusion

In this thesis an ABM of a housing market is developed and fit to local conditions of the Norwegian capital, Oslo. The model comprises of heterogeneous households who interact on the market through purchases of homes and investment houses, a bank responsible for issuing mortgages and dwellings with varying characteristics. The model is spatial, so agents and objects interact in a 2-dimensional world representing the city during the simulation. The model is applied for analyses over a simulation period of 10 years and shown to generate output similar to the historical data. Counterfactual experiments involving tightening of the bank's lending policy and removal of interest deduction is shown to have a stagnating effect on prices. Further, an interest shock imposed on the model yields a significant fall in prices and reduction in the growth of household debt.

Although the attributes and behavioral rules of the agents in the model are based on historical data, further calibration is necessary in order to conduct accurate policy experiments and projections. This is illustrated in the sensitivity analysis where the model is shown to be sensitive to parameters estimated on limited data. Detailed micro data on household and bank behavior could be applied to construct agents closer fit to reality. Further, due to computational restrictions, the model is a small scale version of the market. In theory, an ABM could provide a one-to-one mapping between the market participants and the agents of the simulation.

Other suggestions for further work include exploring opportunities related to the spatial component of the model. For instance, when households search for dwellings on the market, location relative to current home could be taken into consideration. Further, the

model does not capture seasonality, which is an important characteristic of the housing market. This could be implemented by analysing historical data on how household behavior on the market varies with the seasons. Finally, empirical validation techniques for ABMs need further work. In this thesis, mainly qualitative evaluation of model performance has been applied. However, in order to gain increased confidence in the model, formal methods should be developed and applied for testing.

The previous work on ABMs of the housing market is limited and standard economic models such as empirical forecasting models and DSGE models currently dominate the literature. In this thesis it is demonstrated that ABMs facilitate experiments difficult to perform using standard models. Further, many of the characteristics of the housing market, for instance irrational agents with imperfect information, are more easily represented in ABMs than in standard models. Agent-based modelling is a flexible tool with significant potential for representing the complex housing market. While substantial work is necessary before ABMs are recognized as a valid alternative to the standard models applied for decades, this work is hoped to be a step in the right direction.

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Appendix A

Electronic Attachments

The electronic folder attached contains code and data related to:

1. MATLAB files applied for agent generation
 - `initScript.m`: main script for instantiating the model.
 - `createHouseholds.m`: script for generating initial household agents.
 - `createDwellings.m`: script for generating initial dwelling objects.
 - `buildDwellings.m`: script for generating constructed dwellings fed to the simulation.
2. NetLogo file
 - `housingModel.nlogo`: implementation of presented ABM together with necessary data files to execute simulation.