ADVANCING INTEGRATED URBAN MODELLING FOR HOUSING POLICY ANALYSIS

Volume 1: Literature Review

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1 INTRODUCTION

Integrated urban models, also known as integrated land use and transportation models, model the evolution of land use and the built environment over time in an urban region. They are predicated on the understanding that the transportation system (which provides accessibility to land and enables the movement of people, goods and services) and the land use system (which determines the distribution of people, firms and activities over space) are fundamentally intertwined. They can provide essential analytic support for a wide range of urban and transportation policy analyses, notably housing market analysis. The treatment of the housing market in the integrated urban models can be classified based on the spatial resolution for space and agent aggregation for individuals. The most advanced models, known as agent-based microsimulation (ABM) models, look at agents individually at micro level. Space also can be examined at different levels of analysis such as census tracts, traffic analysis zones, buildings, parcels or dwelling units. Modelling the demand, supply and market interactions (including endogenous price formation) within the housing market are core functions within any advanced integrated urban model.

A key component of the housing market which is either ignored completely (the typical case) or (at best) very poorly addressed in all current land use models (including ILUTE and other operational models such as UrbanSim) is the actual financing of housing and its ramifications for ownership and sales. A selling price is typically included in such models and influences in one way or another the allocation of households to dwelling units in such models. But the explicit modelling of how households actually finance housing purchases (down payments, mortgages, impacts of interest rates, etc.) and of the equity which they hold in their homes (and how this equity changes over time and influences subsequent housing mobility decisions) is rarely, if ever, modelled. Given the critical importance that such financial considerations play in housing mobility and purchase decisions, this lack of sensitivity in current models to such considerations clearly represents a major weakness in such models, and considerably limits their usefulness as a policy analysis tool for many housing-related policies of interest to housing market decision-makers and stake-holders.

This report first reviews the housing market modelling in the existing integrated urban models to better understand how these models treat the housing market. Then, in order to identify methods to improve the current housing market models in such models, the report reviews and discusses the macroeconomic housing market literature with a focus on agent-based modelling. Finally, by highlighting the various data sources for Canadian housing market, the report presents conclusions and recommendations for modeling housing market finance in integrated urban models.

2 HOUSING MARKET MODELLING IN EXISTING INTEGRATED TRANSPORT – LAND USE MODELS

The first recognized operational land use model was introduced by Lowry in 1964 (Lowry, 1964). Since then, the evolution and the broadening of the scope of land use models have resulted in not only considering the interaction between land use and transport but also including the influences of economic, social and environmental factors. Several studies provide an overview of current state of integrated land use and transport models (Huang et al., 2014; Iacono et al., 2008; Wegener, 2004). The traditional land use models usually look at the aggregate level of information for both population and land use. However, in order to capture the various interactions and complexity of urban system, a more detailed level of analysis is required. Recently, several models have used the microsimulation agent-based paradigm for integrated urban models. A brief summary of housing market frameworks in the existing integrated urban models with a focus on microsimulation ones is presented in this section.

Most of the integrated urban models consider the housing market at some level. Some models do not differentiate between housing and other land purposes such as firms. Housing market modules in integrated urban models usually consist of four main components: the supply of home locations, the demand for housing, prices and rents, and the assignment of population to residential locations. The majority of integrated urban models include a market for housing in different forms of spatial units such as zone, floorspace, or dwelling unit. Typically in each time period within the simulation, new population is generated and new housing supply is built to accommodate growth in the city. The models usually consider the decision to move or rent and the location choice as the main parts of modeling housing market. Prices are usually modelled endogenously. Most of the models consider market clearing assuming static equilibrium in each time interval, while a few treat the market as being in disequilibrium with delayed price adjustments. The matching process and assignment of households to houses is usually based on some type of willingness to pay or bid-auction method. None of the current integrated urban models take into account the actual financing and purchase procedure of housing market. Table 2.1 provides a summary on the current treatments of housing market by agent-based integrated urban models. In the next section, we further discuss the current ILUTE framework which is one of the first operational agent-based models, developed at the University of Toronto (Salvini and Miller, 2005).

2.1 ILUTE framework

The ILUTE (Integrated Land Use, Transportation, Environment) integrated urban model system provides a fully agent-based microsimulation (ABM) of the urban spatial-temporal socio-economic processes which evolve an urban region over time in response to a wide range of exogenous factors and policy scenarios. Processes modelled within ILUTE presented in Figure 2.1 include:

- Synthesis of a complete base year population of persons, households, buildings, firms, jobs and cars.
- Demographic evolution of the population over time, including evolution of households.
- Firmographic evolution of firms and jobs over time.

- Changes in household auto ownership over time.
- Changes in worker labour market participation (job occupation and industry, location and wages/salaries).
- Evolution of the built space (housing and commercial) over time.
- Daily activity/travel participation by all persons within the urban region.
- The residential housing market.

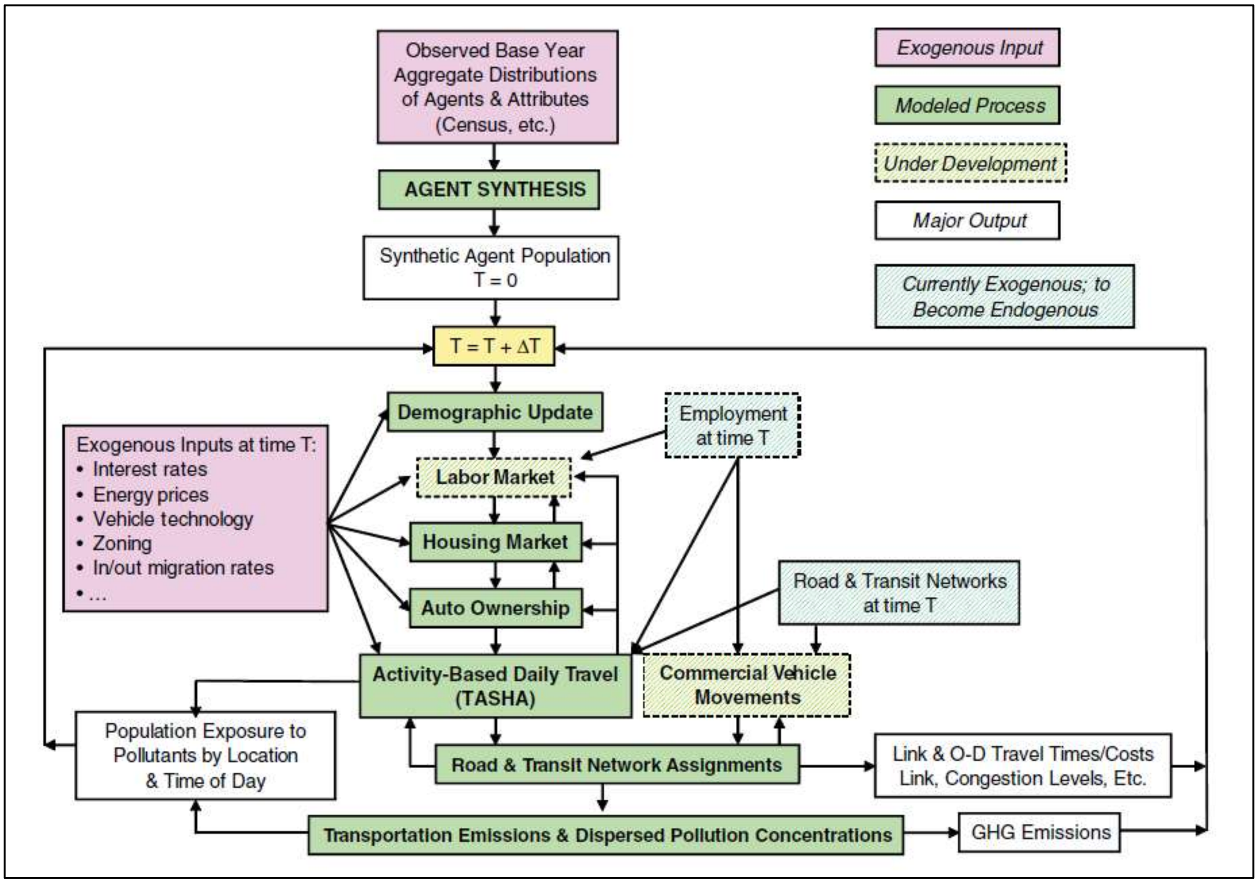

Figure 2.1 The ILUTE framework

The demand-supply interactions within the residential housing market are modelled within ILUTE at the micro level of individual households and dwelling units. As illustrated in *Figure 2.2*, in each time step, each household decides whether to become active in the housing market or not. If it decides to enter the market, it can enter either the rental or owner-occupied housing markets and it competes with other active households in the chosen sub-market for vacant dwellings. Vacant dwellings in the owner-occupied market are auctioned off to the highest bidder for the unit among the households competing for the given unit. Thus, sales prices for each unit transacted are endogenously determined within the model. Households who are unsuccessful over a period of time in the market can leave the market at any time, returning to a "passive" state at their original residential location.

The mobility decision is modeled using a random utility maximization framework in the form of binary logit model with several stressors considered including changes in employment (e.g., gains/losses/changes of jobs), changes in family composition (e.g., childbirth, moving out, aging), duration in current dwelling, and spatiotemporal economic data. The location choice model determines a choice set of active dwellings and the utility of household for each of the dwelling in the choice set using a reference based mixed multinomial logit model. Each property in the active dwelling pool is assigned an asking price. This asking price is based on a multi-level regression model accounting for spatial and temporal factors as well as a set of attributes including dwelling unit characteristics such as size and structure, property location attributes, sale price and average days on market for the type of dwelling, and several macroeconomic indicators such as unemployment rate. On the supply side, a time series model is used to estimate the total number and type of housing built in each year and a logit location choice model is used to allocate the newly created supply to the zones in the region. Matching of active households to the active dwelling pool is done by a market clearing model that auctioning one dwelling unit at a time to competing potential buyers. Market equilibrium is not expected in a given time period.

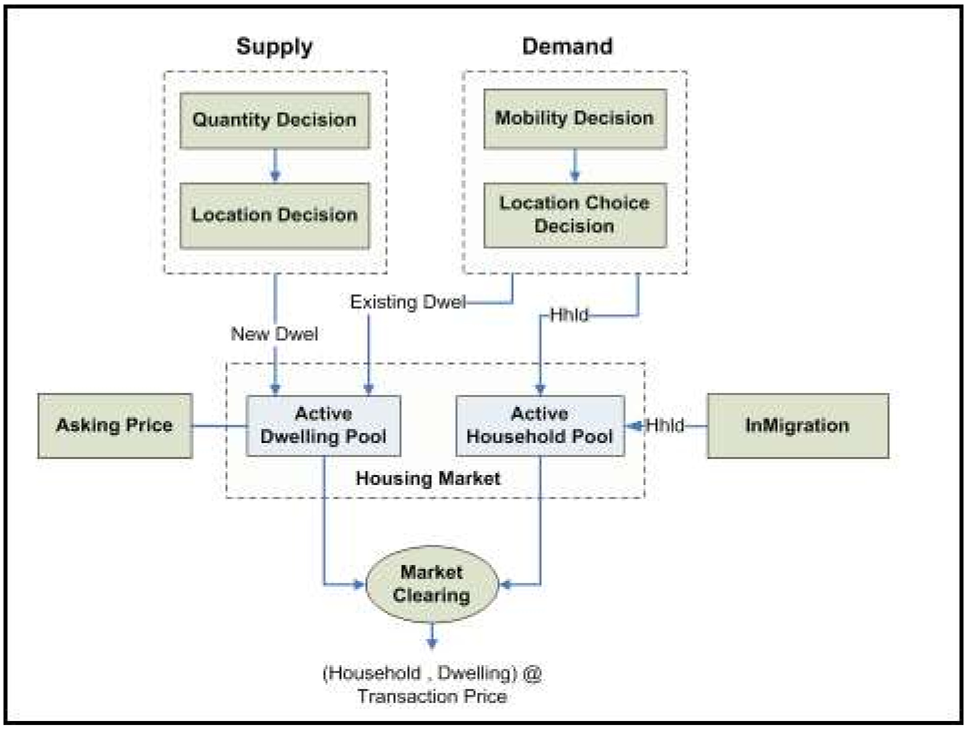

Figure 2.2 The ILUTE Housing Market Model

As seen in this section, the actual housing finance is not considered in any of the current integrated urban models including ILUTE. In the following chapters, we review the models in macroeconomics in order to identify possible methods to add a housing finance module to the current ILUTE framework.

Table 2.1 Housing market in agent-based integrated urban models

Model	Authors	Empirical Setting	Market Clearing	Spatial Unit	Housing Demand	Housing Supply	Housing Location Choice	Price Formation	Matching
ILUTE	(Rosenfield et al., 2013; Salvini and Miller, 2005)	Canada	disequilibrium	Dwelling Units	Residential mobility decision model (Binary-Logit)	Housing Supply Component	Reference-Dependent, Residential location choice (MMNL)	Spatial-temporal multilevel model	Bid-Auction based on endogenous willingness to pay
UrbanSim	(Waddell, 2011, 2002; Waddell et al., 2007)	US	disequilibrium	Parcel (Grid)	Residential location choice (MNL)	Development project location choice models (MNL) Pro Forma developer models	Residential location choice (MNL)	Hedonic Regression Model	Probability-based iterative process with price adjustment
SelfSim	(Zhuge et al., 2016; Zhuge and Shao, 2018)	China	disequilibrium	Nodes of road network	Screening framework based on ranking of households based on inducement and affordability factors	NA	Joint location choice-price formation	Joint location choice-price formation	Rule-based utility (price, accessibility)
ILUMASS (IRPUD)	(Moeckel et al., 2007; Wegener, 2011; Wegener and Spiekermann, 2018)	Germany	disequilibrium	Grid-Zones	Monte Carlo simulation	Monte Carlo simulation	Residential location choice (MNL)	Price adjustment model based on the current price, and the new supply and demand	Rule-based utility (price, accessibility, housing type)
PUMA	(Ettema, 2011; Ettema et al., 2007)	Netherland	disequilibrium	Grid	Residential mobility decision model (Binary-Logit)	NA	Residential location choice (MNL) – search and negotiation system	Probability-based list price	Probability-based (Bayesian learning procedure based on past transactions)
SimDELTA	(Feldman et al., 2010; Simmonds, 1999)	UK	disequilibrium	Ward (Zone)	Monte Carlo simulation	NA	Monte Carlo simulation	Hedonic Regression Model	Rule-based utility (price, accessibility, housing type)

3 A BRIEF REVIEW OF MACROECONOMIC MODELS OF HOUSING MARKETS

Traditional models of housing market assume that housing prices can be derived through supply and demand interactions. The models look at the market at an aggregate level, consider the demand and supply homogenous and ignore the competition in the market. Typically in these types of studies, demand and supply are modelled separately. Housing demand comes from both consumers, i.e. households who want a place within which to live, and investors, who look at housing market as an alternative to the stock market to gain profit. In traditional models, the investor demand usually is treated proportionally to the total demand for housing. The consumer demand for housing is considered as a function of housing price and rent, income, and other fundamental factors such as population, employment rate and interest rate (Mayo, 1981). Supply models of housing market consider new constructions and renovations by developers. They are usually a function of housing prices and construction costs, the rate of new construction and destruction (Ericsson and Hendry, 1985). Having a supply and demand function for housing, the traditional models assume that market reaches equilibrium at each period and calculate the market-clearing housing prices.

Recently, the Dynamic Stochastic General Equilibrium (DSGE) models have become commonly used in the economics housing market literature (Funke and Paetz, 2013; He et al., 2017; Iacoviello, 2005; Iacoviello and Neri, 2010). DSGE models have been found to have more predictive power compared to the traditional models. DSGE models consider agents with preferences which they tend to optimize. DSGE models assume an equilibrium and calculate prices that match supply with demand. A typical DSGE model for a housing market has three main components: demand, supply and monetary policies (Sbordone et al., 2010). Several advantages of DSGE models include providing a flexible framework that can model detailed micro-foundations with the ability to examine shocks. Different types of shocks such as demand shocks, productivity shocks or policy shocks can be incorporated in the DSGE model. A DSGE model contains of a set of equations, which are solved in each period to calculate the equilibrium given that the model needs to fit to the historical data.

The simplified assumptions of the traditional economic models, including DSGE models, can lead to models that are significantly different from reality and thus inaccurate predictions (Farmer and Foley, 2009). The many factors influencing the housing market make it a very complex market with many interactions which are difficult to analyze accurately using aggregate models. A detailed disaggregate framework such as agent-based modelling enables the model to explicitly represent different actors within the housing market. The ability to model the interactions of buyers and sellers in the market can allow for non-linear dynamics, such as housing booms and busts (Baptista et al., 2016; Farmer and Foley, 2009). In the next section, we review agent-based models of housing market in more detail.

4 AGENT BASED MODELS (MACRO & MICROECONOMIC) FOR HOUSING MARKETS

The roots of using agent based modelling in economics goes back the earliest days of digital computing-based modelling (Chapin and Weiss, 1968; Orcutt, 1976, 1957; Orcutt et al., 1961). In the mid-1970s Lucas criticized earlier economics models that did not allow for change in agents' behaviours in response to change in agents' incentives (Lucas, 1976). Building on such early work, more disaggregate models have emerged over time that are based on the design principle that macro-economic behaviour should be built from the bottom up by aggregating the individual actions of self-interested agents. There is a vast body of literature on agent based modeling in economics (for a recent review see (Haldane and Turrell, 2018)). However, the use of agent based models (macro & microeconomic) for housing markets is relatively new. ABM has been used by Wall Street investment banks since the early 1990s to model mortgage prepayment (Geanakoplos et al., 2012). But it was only after the financial crisis and real estate crash in 2007 (and the inability of traditional models to explain those phenomena) that the ABM received increased attention in housing market modelling.

In a typical housing market, many complex decisions and interactions exist. For example, households need to decide whether to buy or rent, how much to pay, type of mortgage and amount of down payment, and when to buy or sell. On the other side, banks need to choose their mortgage policies and prices, how much leverage to permit, and methods for evaluation of households' credit. ABMs were well suited to dealing with this complexity and heterogeneity. While the concept of modelling housing markets using ABM goes back at least 32 years, the first paper with an actual empirical setting is from the UK housing market, developed by Gilbert et al. in 2009 (Gilbert et al., 2009). Since then, there have been a handful of studies in the economics/computer science literature that used ABM to model housing markets. These studies are reviewed in this section.

Traditional macroeconomic models lack the capability to account for the complexity of the housing market and therefore cannot predict the formation of a housing bubble. Thus, the majority of the housing market ABMs in the economics literature aim to better understand and model housing prices and the market's bust and boom cycles. These models typically use heterogeneous agents as buyers to model housing prices (Burnside et al., 2011; Dieci and Westerhoff, 2013; Eichholtz et al., 2014; Geanakoplos et al., 2012; Kouwenberg and Zwinkels, 2015). In particular, these models distinguish between different drivers of housing prices. It is shown that housing prices derive from both fundamental factors (such as supply, demand, tax structures, and interest rates) and the momentum of recent trends. Some recent studies calculate the prices by probabilistically weighting the price for agents based on these two types of factors (Bolt et al., 2014; Chia et al., 2017; Eichholtz et al., 2014).

Several studies consider and model the different agents involved in the housing market. Using data from the UK housing market, the ABM by Gilbert et al (2009) considers sellers, buyers and realtors, along with a set of exogenous macroeconomic variables such as interest rate. The model has a spatial interface using a grid system, along with a simple transaction module for market clearing and a new-build and demolition module for creating new supply (Gilbert et al., 2009). Several recent studies extend the ABM for housing markets to include banks and mortgages as agents in addition to the households and houses. While these models are more advanced with various finance components such as mortgages and interest rates, they lack neighbourhood attributes and/or a spatial structure (Axtell et al., 2014; Baptista et al., 2016; Carstensen, 2015; Goldstein, 2017). A recent study of the housing market in Oslo, Norway used the platform developed in Gilbert et al. (Gilbert et al., 2009) and enhanced the financing components of the model (Ustvedt, 2016). More recently, Pangallo et al. (2017) developed an ABM for a housing market considering a grid structure for spatial representation to investigate spatial income segregation and inequality. As the purpose of their work is to show the capability of ABM to analyze segregation, the model is simplified and only has households - buyers, housed, sellers - as agents without any demographic, bank or supply component (Pangallo et al., 2017). Recently, Ge (2017) developed an ABM model with a spatial structure that accommodates most of the finance component of the housing market, including regular and speculator households, and has modules for banks, mortgages and developers. The main drawback of the model is that the population characteristics such as income and demographic attributes are assumed exogenous (Ge, 2017).

Table 4.1 presents a summary of housing market ABMs in the current economics literature. In these studies, housing prices are generated endogenously, and some type of market clearing mechanism, such as auction bid, is used. All of the ABMs consider some sorts of agents for buyers and sellers. Several of them include the rental market in the modelling as well. Most of the studies have a "bank agent" which generates and sets the criteria for loans and mortgages required for buying a house on the market. Several of the models consider a type of supply model to account for developers who add supply to the housing market.

Table 4.1 Summary of agent-based models in economics

Authors	Year	Empirical Setting	Model Characteristics	Spatial Structure	Type of Household	Demographics & Income	Mortgage	Supply
Gilbert et al.	2009	UK	**Households,** **Realtors**: setting prices.	Grid	Buyer, Seller	No	No	Yes
Axtell et al.	2014	US	**Households**, **Banks**: generate loans, handles defaults and foreclosures, **Houses**: built, destroyed, bought, sold, rented, and lived, **Loans**: fixed, adjustable-rate, and interest-only.	Non	Buyer, Seller, Renter	Yes	Yes	Yes
Carstensen	2015	Denmark	**Households** **Banks**: generate mortgages	Non	Buyer, Seller, Renter	Yes	Yes	No
Baptista et al.	2016	UK	**Households**, **Banks**: mortgage type and interest rate **Central Bank**: core indicators and mortgage regulations	Non	First-time buyer, Owner occupiers, Buy-to-let investors, Renter	Yes	Yes	Yes
Ustvedt	2016	Norway	**Households** **Banks**: generate mortgages	Grid	Buyer, Seller, Renter	Yes	Yes	No

Goldstein	2017	US	**Households** **Houses**: built, destroyed, bought, sold, rented, and lived. **Loans**: fixed, adjustable-rate, and interest-only	Non	Buyer, Seller, Renter	Yes	Yes	Yes
Pangallo et al.	2017	Non	**Households**	Grid	Buyer, Seller	No	No	No
Ge	2017	US	**Households** **Banks**: generate loans, handles defaults and foreclosures **Developer**: build new house	Grid	Buyer, Seller (regular or speculator)	No	Yes	Yes

The following paragraphs focus on three of these studies that are deemed to be most relevant to our project.

The first study is done by **Baptista et al. (2016)** for the Bank of England. It examines the UK housing market using an agent-based model to investigate the impact of different monetary policies. In their model, there are three types of agents: (i) households, (ii) a bank (mortgage lender), and (iii) a central bank. Households are the main agents in the model and differ along several attributes such as age, income, and bank balances. Each period, some households die, are born or age, while receiving and consuming income and making decisions concerning their housing state. There are four types of households: renters, first-time buyers, owner occupiers, and buy-to-let (BTL) investors. The BTL investors are in fact some of the households that are randomly selected to have the ability to buy and sell additional properties which can also be rented to other households. When buying houses, households can take out mortgages from a bank which represents the mortgage lending sector. The mortgage market is subject to regulation by a central bank that sets macro-prudential policies. Figure 4.1 A schematic of Baptista et al. (2016) modelFigure 4.1 shows a schematic of their model and the interactions between the modules.

In the model, housing decisions depend on the current state of the household (i.e. whether they are in social housing, renting, or owning-occupying). For each state, a set of rules and equations define the housing decisions for the household. Those households who decide to buy need to finance their purchases either using a mortgage or cash. It is assumed that if the buyers have a wealth greater than twice the house price, they pay by cash; otherwise, they must request a mortgage and pay a down-payment. The type of mortgages and amount of down-payment is set by the bank module. The bank considers loan-to-value (LTV), loan-to-income (LTI) and affordability criteria (for investors, an interest cover ratio (ICR) constraint is also added) for approving mortgages to the potential buyers. The amount of down-payment is based on the income of the household, house price and a distribution factor from the observed data of down-payments. Interest rates are calculated based on an exogenous bank rate plus the spread. The interest rate spread is calculated each month as a function of total supply of mortgage lending in the month and an exogenous constant target monthly supply. The Central Bank defines the policies by setting different thresholds for the LTV, LTI and ICR and affordability policies.

The model is calibrated at both micro and macro levels. First, a micro-calibration is done that fine-tunes households' characteristics directly against micro data, mostly from household surveys and housing market data sources. Then, a macro-calibration that ensures consistency with relevant economic aggregate indicators is performed. The model results are promising with the ability to predict the housing booms and busts. The results highlighted that buy-to-let investors can influence house price cycles. The study finds a loan-to-income limit for mortgages a reasonable policy to control the house price cycle.

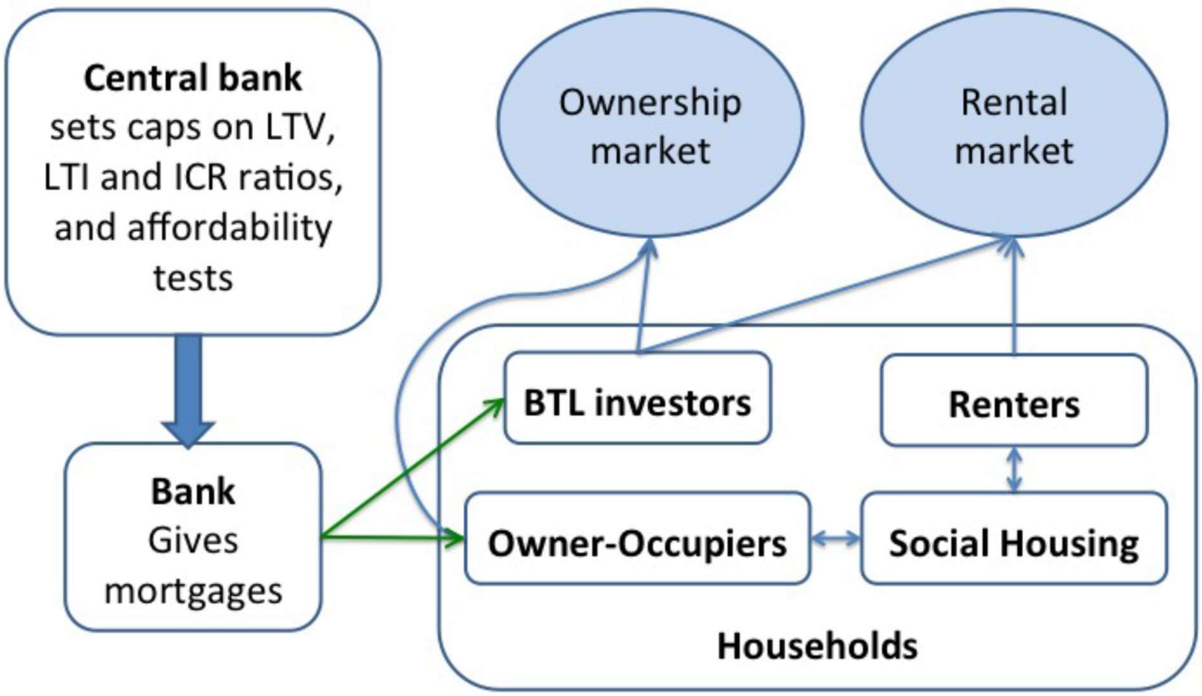

Figure 4.1 A schematic of Baptista et al. (2016) model (Baptista et al., 2016)

A dissertation by **Goldstein (2017)** examines the Washington DC housing market from 1997-2009 using agent-based models (part of his dissertation is also published in (Axtell et al., 2014)). Goldstein's model uses several micro-data sets as input, including detailed records of real estate listings and transactions, home ownership and vacancy rates, monthly data on loans, household demographics and income, and historical data for house prices and mortgage prime rates. The model consists of only one type of household (agent) with different demographic attributes. The model is executed in monthly time intervals. In each month, the population is updated to match the region's demographic data and to perform non-interactive actions, such as accruing wealth, listing their houses, refinancing, defaulting, etc. The model also updates the housing supply based on input data. Finally, in each month, agents can buy, sell or rent houses. Loans in the model are one of three types: fixed rate, adjustable rate (ARM), and interest-only. Figure 4.2 diplays the interactions between the different modules in Goldstein model.

In the simulation, the model tries to match the empirical data with respect to the aggregate distribution of loan types (conditional on debt-to income ratio) and interest rates (conditional on loan type and debt-to-income ratio). Households make a decision to refinance, list their house or buy a house in each period. The refinancing probability depends mainly on LTV. While the probability to enter the housing market is based on age, the decision to list a house is set randomly with the constraint that the number of listed houses matches empirical data. The down-payment is based on the desired home price and a desired LTV. The type of loans and interest rate are chosen based on historical frequencies depending on LTV and debt-to-income.

The model is used to investigate the underlying causes of the 2007 housing crisis. The results show that the ABM model is not only able to meet the output distributions such as distribution of house prices but also to generate both macro indicators such as the shape of house price index and intermediate attributes such as distribution of loan types or average days on market. The dissertation also presents a sensitivity analysis by changing the model parameters as well as the model's structural rules.

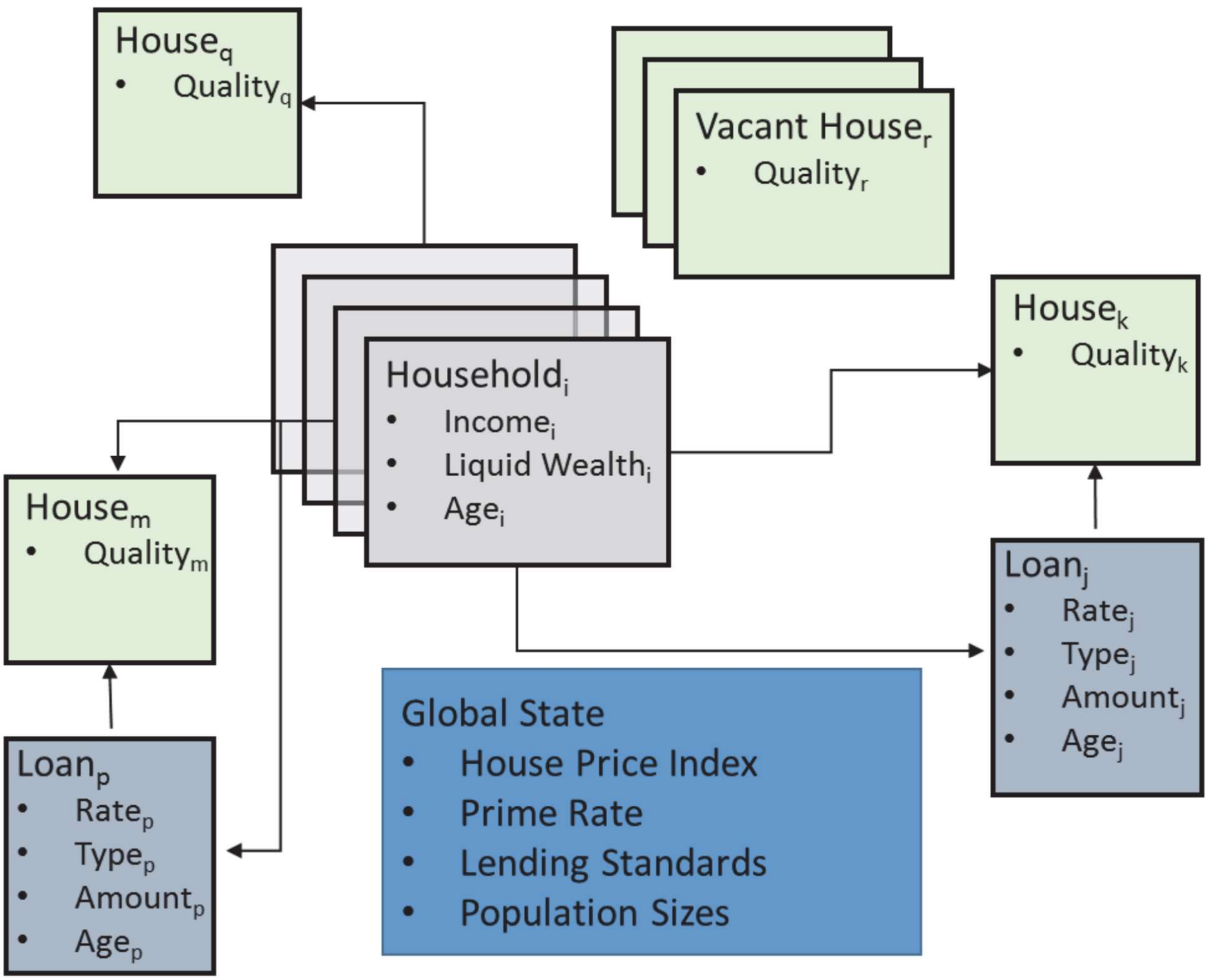

Figure 4.2 A schematic of the Goldstien (2017) model (Goldstein, 2017)

The last paper reviewed in this section is by **Ge (2017).** The paper introduces a spatial structure to the typical finance components of the abovementioned models. The agents in the model include households (regular or speculator), bank, one aggregate developer, who builds the supply endogenously, and one real estate agent who settles the market price. Figure 4.3 demonstrate the

ABM framework used in Ge's model. Time is set at the monthly level and the landscape is defined at a neighbourhood level using a 5×5 grid (25 neighbourhood) system. Each neighbourhood then has an exogenous location quality index as well as an endogenous quality index defined, mainly based on the demographics and income of its residents.

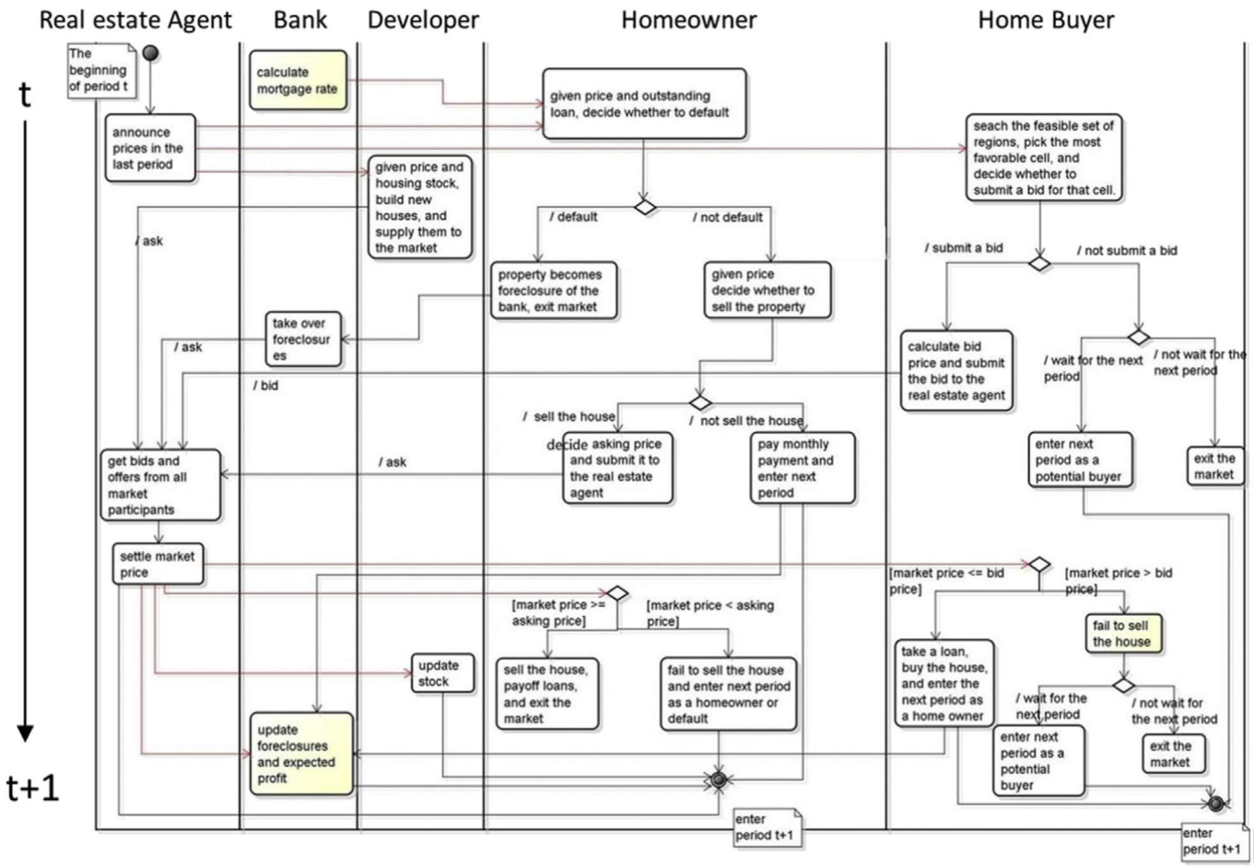

Figure 4.3 A schematic of Ge (2017) model (Ge, 2017)

Mortgages for households to buy a property are considered based on the debt-to-income ratio, amount of down-payment, LTV, price and interest rate. Developers build new supply endogenously based on the construction costs and housing prices. The developer agent is assumed to maximize its profit. The real-estate agent sest the price based on the bids received and asking prices. This price formation process is presented in Figure 4.4. Two types of agents represent households: regular buyers and speculators. These two types differ in terms of their property search. The regular buyers try to maximize the gained utility by buying a house. Thus, they care about neighbourhood quality, location quality and consider the affordability of the housing unit. On the other hand, speculators buy a property to make a profit. Therefore, they consider properties that can return the highest expected profit, which is determined by the expected price inflation in the region and the mortgage rate. The model is tested using 2007-2009 US housing data in order to better understand the cause of housing market collapse and identify policies that could mitigate such phenomena.

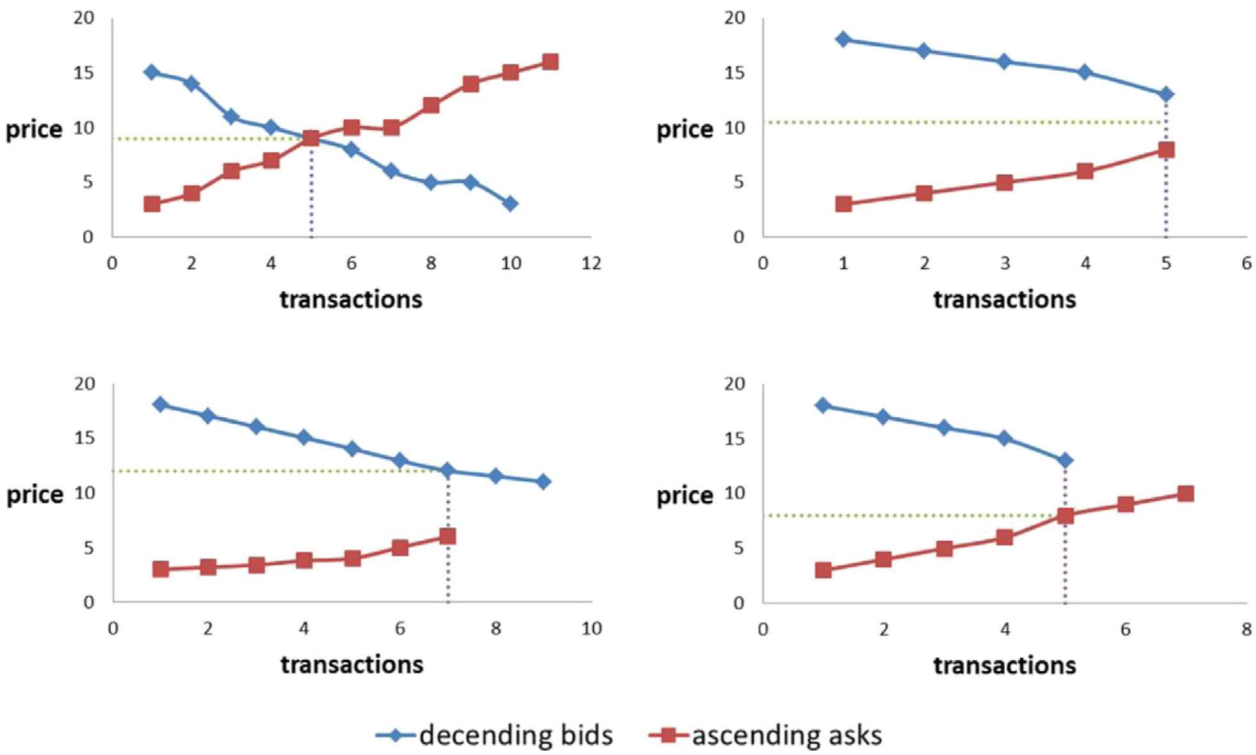

Figure 4.4 Price formation process of Ge's model (Ge, 2017)

5 CANADIAN DATA SOURCES FOR HOUSING MARKET MODELLING, INCLUDING FINANCING CONSIDERATIONS

This literature review indicates that there is not any agent-based model developed specifically for the Canadian housing market that accounts for the housing financing. While the ILUTE model developed for the Toronto region models its housing market, the finance component of the model is relatively simple. The current ILUTE framework makes use of the following datasets among others for modelling housing market:

- Statistic Canada census: most of the socio-demographic attributes in ILUTE are based on the census.
- Toronto Real Estate Board (TREB) database: the dataset contains historical data of all Multiple Listing Sales (MLS) listings and sales.
- Residential Mobility Survey (RMS II) for the Toronto region: the survey provides a rich panel dataset respondents housing careers.
- Transportation Tomorrow Survey: The household travel survey conducted every five years in the Toronto Region.

There are other possible sources of data that can be used to enhance the current ILUTE models including:

- Statistic Canada Survey of Financial Security (SFS): the dataset provide a comprehensive data for household demographics as well as their assets, debts, employment, income and education.
- Teranet property transactions data. UTTRI has recently acquired a three-year license to use the Teranet database for the Greater Golden Horseshoe (GGH).

The SFS, in particular, provides an exceptional database for developing a model of housing financing suitable for incorporation within a housing market ABM such a ILUTE.

6 CONCLUSIONS

Current integrated urban models, such as UrbanSim, PECAS and ILUTE, do not consider the actual financing of housing and its ramifications for ownership and sales in their housing market components. On the other hand, there has been an increasing number of studies in the macroeconomic literature focusing on agent-based models to better understand the housing market and its complexity, including financing considerations. However, these models are not as advanced as integrated urban models in terms of spatial structure, consideration of accessibility and transportation impacts, and modelling demographics and jobs. Bridging these two area of research by adding a housing finance module based on the agent-based models in macroeconomics to the current integrated urban models such as ILUTE will improve both types of models, resulting in a more accurate representation of the actual complex interactions of housing market. Such a model would also allow better identification the role of different contributing factors with housing market evolution, such as mortgage rules or transportation infrastructure.

In the Volume 2 of this report, we will propose a framework to improve the current housing market module in ILUTE by adding housing financing components. This proposed work will build heavily upon the Statistics Canada Survey of Financial Security, which appears to provide an excellent database for this research.

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