Arab Journal of
Administrative Sciences

2025, Vol. 32, No. 2, 389-433
Doi: 10.34120/ajas.2025.1281

Ebrahim Alebrahim
Kuwait University
Kuwait

Agent-Based Models in Industrial Economics: A Perspective of the Kuwaiti Housing Market Structure

Abstract

Purpose: This study provides an introduction to the agent-based modeling approach in industrial economics, with a focus on the Kuwaiti housing market structure. It develops and analyzes an illustrative agent-based market model.
Study design/methodology/approach: We construct an agent-based model to study the effects of search costs and the number of speculators on housing price volatility. We also illustrate the agent-based modeling process using NetLogo and R.
Sample and data: Our data consists of housing-related policies passed in Kuwait over the last two decades. We discuss relevant studies from industrial economics and housing literature based on their applicability to Kuwait's housing market structure.
Results: Our findings suggest that both lower search costs and a higher number of speculators lead to lower price volatility. We also demonstrated that agent-based modeling has significant potential for assessing policy impacts on housing markets. Features from other industrial economics models can be incorporated into the Kuwaiti housing market framework.
Originality/value: This study bridges a gap in the literature by demonstrating how agent-based models can enhance understanding of policy effects on Kuwait's housing market structure. It also highlights the benefits of integrating elements from industrial economics models into agent-based housing models.
Research limitations/implications: While agent-based models offer potential applications in Kuwait, their design, testing, and validation require interdisciplinary efforts.

Keywords: Agent-Based Models, Industrial Economics, Housing Market Structure, Kuwait.
JEL classification: R21, R31, C63, L11, L51

Submitted: 28/11/2024, revised: 13/1/2025, accepted: 26/2/2025.

To cite: Alebrahim, E. (2025). Agent-based models in industrial economics: A perspective of the Kuwaiti housing market structure. *Arab Journal of Administrative Sciences*, *32*(2), 389-433.
https://doi.org/10.34120/ajas.2025.1281

الملخص

النماذج القائمة على الوكلاء في الاقتصاد الصناعي: نظرة في هيكل سوق العقار السكني في الكويت

إبراهيم الإبراهيم

جامعة الكويت، الكويت

هدف الدراسة: تهدف هذه الدراسة إلى تقديم نهج النمذجة القائمة على الوكلاء (Agent-Based Model) في الاقتصاد الصناعي (Industrial Economics)، مع التركيز على هيكل سوق الإسكان الكويتي، إضافةً إلى تطوير وتحليل نموذج سوقي توضيحي قائم على الوكلاء. ويجري ذلك على هيكل سوق الإسكان الكويتية خاصةً.

تصميم/ منهجية/ طريقة الدراسة: تقوم الدراسة على بناء نموذج قائم على الوكلاء لدراسة تأثير تكلفة عملية البحث عن السكن، وكذلك عدد المضاربين على درجة تقلب أسعار الإسكان. يوضح النموذج عملية النمذجة القائمة على الوكلاء باستخدام (NetLogo) ولغة (R).

عينة الدراسة وبياناتها: تتكون بيانات الدراسة من القوانين والسياسات المتعلقة بالإسكان، والتي أُقرّتْ في العقدين الماضيين في الكويت، إضافةً إلى اختيار ومناقشة الدراسات في مجال الاقتصاد الصناعي والإسكان بناءً على إمكاناتها في نمذجة الجوانب المختلفة لهيكل سوق الإسكان في الكويت.

نتائج الدراسة: تشير نتائج الدراسة إلى أنّ كلًا من انخفاض تكاليف البحث عن سكن، والزيادة في عدد المضاربين في السوق، يؤدّيان إلى تقلبات أقل في الأسعار. كما تبين أنّ نهج النمذجة القائمة على الوكلاء يتمتع بإمكانات كبيرة في تقييم تأثير السياسات على أسواق الإسكان، وكذلك توضح كيفية دمج خصائص من نماذج الاقتصاد الصناعي الأخرى في إطار نمذجة سوق الإسكان الكويتية.

أصالة الدراسة: تسد هذه الدراسة الفجوة البحثية عن طريق مناقشة كيفية استخدام النماذج القائمة على الوكلاء وخصائص نماذج الوكلاء الخاصة بالاقتصاد الصناعي لبناء نماذج تعزز فهم تأثير التغييرات في القوانين على هيكل سوق الإسكان الكويتي.

حدود الدراسة وتطبيقاتها: على الرغم من الإمكانيات الكبيرة لتطبيق النماذج القائمة على الوكلاء في السوق الكويتية، فإن تصميمها واختبارها والتحقق من صحتها تتطلب جهودًا متعددة التخصصات.

الكلمات المفتاحية: النماذج القائمة على الوكلاء، الاقتصاد الصناعي، هيكل سوق الإسكان، الكويت.

الإشارة المرجعية: الإبراهيم، إبراهيم. (2025). النماذج القائمة على الوكلاء في الاقتصاد الصناعي: نظرة في هيكل سوق العقار السكني في الكويت. *المجلة العربية للعلوم الإدارية*، *32*(2)، 389-433.

https://doi.org/10.34120/ajas.2025.1281

Introduction

How can researchers and policymakers understand complex market dynamics when data is not available? While economics research is dominated by empirical studies (Paldam, 2021), many important questions suffer from data limitations. Although experiments and surveys may fill some of the gaps, simulation-based models can be powerful tools to study phenomena in a controlled environment.

Unlike mathematical models, simulation models are known for their flexibility and their ability to incorporate many real-life nuances and details. System dynamics, discrete event simulations, and agent-based models are the main simulation-based methodologies. The system dynamics approach relies on modeling stock and flow aggregate variables as a system of ordinary differential or difference equations. The discrete event simulation models a system as a sequence of discrete events. The agent-based models are based on interactions of agents in an environment, making them more suitable for understanding complex markets and emergent behaviour.

This paper aims to provide an introduction to Agent-Based Models (ABM), and their applications to industrial economics and market analysis. We first discuss the history and the rationale behind ABM with some seminal examples and models, and then explore the role of ABM in policymaking.

Additionally, we devote a special section to the potential application of agent-based modelling in the Kuwaiti housing market. We first provide an overview of the real-estate policy changes passed by the legislature over the last two decades. Second, we discuss how such policy changes could affect the housing market, illustrating the potential use of agent-based models. More specifically, we discuss how features from some of the models in the literature can be incorporated into agent-based models to address and understand the effect of the policy changes in the housing market. Furthermore, we provide a brief overview of the agent-based modelling tools and illustrate how to build a simple agent-based market model. Additionally, we show how to analyse our model in R language. We also show that our stylized model reveals some useful insights for the policymaker.

We structured the paper by, first, discussing the rationale and the role of agent-based models in modeling complex systems followed by examples of their applications in industrial economics with attention to the housing market. Next, we provide an overview of the Kuwaiti housing market structure with emphasis on the potential applications of agent-based models in understanding market dynamics under the limitation of data availability. We then construct an illustrative market-based agent-based model and discuss its building process and the analysis of its results. Finally, we conclude with the implications of our results and a discussion of the general agent-based modeling process and potential future applications.

Complex Systems and Agent-Based Model

If one's objective is to find the correct model of what they study, then they are undoubtedly on the wrong path as all models are, in principle, wrong (Box, 1976). Agent-based models are no exception to that. However, ABMs can provide useful insights into complex systems for which pure mathematical modelling methods might not be feasible. A complex system is a system that can be analyzed into many interrelated components, where the behavior of each component depends on the behavior of others (Simon, 1962). Alternatively, a complex system is a system where its outcomes cannot be understood by the understanding of the behavior of the parts. The fact that a complex system could have many components that depend on their behaviors of the behavior of the others makes many of them hard to be modeled by pure mathematical and statistical models, even though the parts of the complex system themselves could be simple. Here is where the use of ABMs is most useful or even might be the only way to go. An agent-based model is a model that consists of interacting agents where the outcomes of the interaction cannot be deduced by understanding the behavior of the agents separately (Axelrod & Tesfatsion, 2006).

Although the use of ABMs in economics is relatively recent, the notion of complexity in economic systems goes as far as the 19th century. For example, the notion of the "invisible hand," introduced by Adam Smith in his famous book "Wealth of Nations," is simply a notion of a complex system (Heath & Hill, 2008).

The notion of complexity does not necessarily mean a complicated system. An example from ecology can illustrate this. It has been believed for a long while that the flocking behavior of birds is a result of a leadership position of some birds in the group. Contrary to that belief, using a computer simulation, Reynolds (1987) has shown that if birds follow three simple rules: collision avoidance, velocity matching, and flock cantering, flocking behavior will emerge without needing the leadership rule. Although the model is simple, it is of a complex nature. Another well-known, abstract and simple model that illustrates the concept of complexity is the cellular automaton model invented by the mathematician John Conway, which is known as “Conway’s Game of Life” (Gardner, 1970). This game has no players and consists of cells on a rectangular grid. The game is governed by three simple rules. Given those simple rules and the current cellular state, a complex dynamic behavior could emerge. The two previous examples illustrate that what is meant by complexity in complex systems is the complexity in the emergent behavior rather than the complexity of the model itself. That is, one cannot simply predict the emergence of, for example, the flocking behavior by merely understanding the three simple rules followed by each bird.

A very early agent-based model in economics is Schelling’s segregation model (Schelling, 1978). Schelling (1978) proposes two main versions of his model. One is a linear model, and the other is a two-dimensional model. In both versions, there are two types of agents. Each type follows certain simple rules. Schelling explains that the model starts with a state where agents are distributed randomly on a grid or a line, then he shows that when agents follow the rules, which does not necessarily favor segregation, they eventually reach a segregation equilibrium of clustered areas, with each consisting of only one type of agent.

Applications of Agent-Based-Modelling

Agent-based models can be built to understand a system at different levels. For example, we can use them to understand how the interactions of agents in a certain market affect the wealth of each agent or agent type or even the behavior of agents. Additionally, we can use the model to understand the dynamics of market-level variables, such as prices. From a macroeconomic perspective, the model can be used to understand macroeconomic variables such as unemployment or inflation. Hence, agent-based models can be built to understand both micro and macro-level phenomena.

Agent-based models have been widely applied in economics and business fields. Auctions are among the areas that have attracted considerable attention. There are many auction designs that economic theory offers limited understanding of. The multiple bid auctions, where multiple units are bought or sold, is an example of that (Hailu & Thoyer, 2007). Hailu and Thoyer (2007) study the performance of three pricing formats in multiple bid auctions. Their model consists of a single buyer, the government, and multiple bidders who provide their supply schedule. Bidders are involved in repeated auctions and refine their supply functions to maximize their income through reinforcement learning.

Agent-based modelling has been used to test auction mechanisms. For example, Araúzo et al. (2018) built a model to test a proposed auction mechanism for allocating airport slots. Esmaeili Avval et al. (2022) built a multi-agent model to investigate different auction designs in the carbon emission market.

Common-value auctions with learning is another topic that has attracted the attention of economists. Experimental studies show that bidders adapt their behaviour in common-value auctions (Kagel & Dyer, 1988). Motivated by Kagel and Dyer (1988)'s findings, Andreoni and Miller (1995) created an agent-based model that aims to understand the common-value auctions with learning agents. Noe et al. (2012) extend Andreoni and Miller's (1995) work by introducing uncertainty in goods value. Reserve prices on first-price common-value auctions have had less attention in the auction literature. This is partly due to the mathematical difficulty in modelling it (Boyer & Brorsen, 2014). Boyer and Brorsen (2014) have approached such auctions using an agent-based approach with the particle swarm learning algorithm. They have found that the bidding equilibrium price and seller's expected revenue in a two-buyer auction with a reserve price is higher than without a reserve price. However, the probability of selling the item is lower in the reserve price case than without it.

Other works have studied the effect of convex incentives on the financial market by building an agent-based model of a double auction market in which some agents are endowed with convex contracts Fabretti and Herzel (2017). Fabretti and Herzel (2017) have found that convex incentives introduce instability and inefficiency in the market.

Other researchers focused on testing methodologies of auction agent-based models. In pure mathematical models, the researchers first build a model of a problem of interest, and based on that model, they postulate some hypotheses that can be tested econometrically. In an agent-based model, the researcher instead calculates some statistics from the model's results and tests the model's performance by comparing the model's generated statistics with actual data statistics. Tseng et al. (2010) show how agent-based auction models can be statistically tested. The authors build three types of agent-based models of continuous double-auction: a zero-intelligent agent model, a zero-intelligent-plus model, and a Gjerstad–Dickhaut model. Interestingly, using Taiwan Political Exchange (TAIPEX) market data, and testing for certain properties from the market, they have found that the zero-intelligent agent model is the best in describing those properties.

The interplay of innovation, market dynamics, entry and exit decisions, and market structure is a topic that has attracted the attention of economists since the seminal work of Nelson and Winter (1985). Cantner and Pyka (1998), Dawid and Reimann (2005), and Silverberg and Verspagen (1994) are among the earlier works on evolutionary economics and market dynamics using agent-based models. A study by Silverberg and Verspagen's (1994) aimed to build a model with endogenous growth. Their model consists of firms with learning capacity that exhibit a steady-state growth path. Cantner and Pyka (1998) focus on creating a model with an endogenous spillover effect. Their model consists of heterogeneous learning firms competing in an oligopoly market. Dawid and Reimann (2005) construct a model that aims to understand firms' decisions on innovation, market entry, exit, and output. A distinct feature of their model is that firms make their decision based on their market evaluation. Firms evaluate the market based on three main factors: market potential, growth rate, and profitability (Dawid & Reimann, 2005; Hax & Majluf, 1983).

Agent-based models have also been used to model firms' competition in more complex settings. Catullo (2013) has built an agent-based model to study the relationship between exporters' premia and firms' monopolistic competition in the international trade market. An interesting feature of this model is that firm heterogeneity emerges due to firms' interactions.

One question of primary interest in the price competition and anti-trust field is the welfare effect of price competition. Zhang et al. (2008) have built an agent-based model that considers the welfare effect of price competition, product differentiation, and consumer heterogeneity in a single framework. The model is applied in the transportation network. Their results favour a fixed-rate pricing policy over a flexible pricing policy. Rahimiyan and Rajabi Mashhadi (2010) employs an agent-based model to explore the effect of divestiture policies on competitiveness in the electricity market.

Some of the more recent studies focus on the effect of the penetration of Artificial Intelligence (AI) technologies on industry structure. For example, Dawid and Neugart (2023) exploits agent-based models to explore the impact of AI on industry structure variables such as wage distribution, labor share, and output. More specifically, they pay special attention to the interplay of market competitiveness on the aforementioned variables. Borsato and Lorentz (2023) create a model that explores the effect of AI on the data production market. The study focuses on aspects such as productivity, product quality, and market structure.

Spatial and location decisions made by firms are another area of interest in the area of competition. Hotelling's model of spatial competition is a fundamental, well-known model in that area. Despite their usefulness, most spatial models assumed away many real-life features. Relaxing and testing many assumptions can be very challenging using a pure mathematical modelling approach. One topic that has attracted extensive attention from economists is the price spatial linkage (Fackler & Goodwin, 2001). It is essential for understanding many market aspects, such as market definition, antitrust regulation, and market integration (Fackler & Goodwin, 2001).

While the price spatial linkage has attracted the attention of economists, the endogenous nature of price has attracted little attention (Sanchez-Cartas, 2018). The study by van Leeuwen and Lijesen (2016) is one of the early works that attempts to build an agent-based model of spatial and price competition. Their model is built to understand the effect of relaxing some potentially restrictive assumptions, such as the assumption of homogeneity of firms and consumers.

A distinguished feature of that paper is that it starts from the bottom up. The authors first give a concise introduction to the agent-based models and spatial competition models, and then they precisely describe Hotelling's model from the game-theoretic perspective. After that, they lay out the agent-based model setup, followed by the results and model validation process. This paper's precise and concise structure makes it one of the good-to-start-with papers for new-to-the-area economists who seek to use an agent-based modelling approach.

Sanchez-Cartas (2018) models price competition in a multi-market pricing situation. Their work shares a common ground with van Leeuwen and Lijesen (2016) by modelling an endogenous price competition. However, Sanchez-Cartas (2018)'s model is more general and can be applied to different market setups than van Leeuwen and Lijesen (2016) 's.

Other studies focused on extending the classical Hotelling model. For example, Ottino-Loffler et al. (2017) extend Hotelling's model to a two-dimensional world with more than two firms. The model allows a non-uniform distribution of the firms. It exhibits interesting emergent behavior. Contrary to the minimum differentiation principle observed in the basic Hotelling's model, firms are involved in local duopolies. Additionally, they observe heterogeneity in price and non-uniform distribution of firms.

Agent-based models have many applications in the housing market. For example, the model of Gilbert et al. (2009) is among the early agent-based models that attempt to model a housing market. Their model is a simplified representation of the English housing market. It consists of three types of agents: buyers, sellers, and realtors. The authors illustrate how the model can be used to explore the effect of interest rate and loan-to-value ratio on house prices using some hypothetical model parameters. Magliocca et al. (2011) build a more specialized model that explores the interplay of land and housing markets. Their model can be used to understand how land-use policies affect housing development and land prices.

Later works attempt to build models calibrated with real market data. For example, Axtell et al. (2014) created a housing market model for the Washington D.C. area that aims at understanding the causes of housing price bubbles. Baptista et al. (2016) extend the works of Axtell et al. (2014) to the UK market. Their study explores the effect of macro-prudential policies on the UK housing market. More specifically, they explore the effect of the size of the rental on buy-to-let, buy-to-let sectors, and a loan-to-income limit on the house price cycle. Pangallo et al. (2019) build a model to explore the relationship between income inequality and segregation in the housing market and the implication of taxes and subsidies on social mixing. Evans et al. (2023) created a model for understanding the effect of decision-making behaviors on the Greater Sydney housing market. Their model is spatial and calibrated with Sydney market data.

Alghais and Pullar (2018) utilize an agent-based modelling approach for understanding housing and urban planning in Kuwait. Motivated by the rapid population growth in Kuwait, they created a spatial agent-based model to forecast the impact of population growth on housing shortage and traffic congestion.

More recent work aims to build more sophisticated models. For example, Mérő et al. (2023) extend the work of both Axtell et al. (2014) and Baptista et al. (2016) to the Hungarian housing market. They construct a more detailed market model, considering the credit market and the construction sector.

We aim to extend the literature by focusing on the Kuwaiti housing market. We first provide an overview of the Kuwaiti housing market and the recent regulatory changes. Furthermore, we provide direction on the potential use of agent-based models in understanding the effect of the regulatory changes on the market. Additionally, we build and analyze a simple market model and use it to illustrate the process of agent-based model building using NetLogo.

Kuwaiti Housing Market

Despite the severity of housing affordability in Kuwait, there are, in general, limited studies that address and synthesize the different dimensions of it. In this section, we first aim to provide a short overview of the residential market in Kuwait. Second, we will discuss the affordability of housing in Kuwait and the laws that have been passed that could potentially affect it. Last, we discuss the role that agent-based modelling can play in enhancing the understanding of the residential market dynamics, the effect of the passed laws, and the potential of future policies.

Residential lands, and more generally, areas in Kuwait, can be classified into two types: Investment residential lands and low-density, or single-family, lands. Investment lands are where apartment buildings can be developed, while low-density lands are designated for single-home developments. Investors can be classified into two types: individual investors and corporate investors. Individual investors invest in and develop lands in their name. Corporate investors invest under some corporate entities, such as limited liability companies.

Kuwait has suffered from a rapid increase in housing prices that outpaced the rise in income during the last two decades (Alfalah et al., 2023). The legislature passed several laws related to housing during that period, as shown in Table 1.

Table 1
Summary of Housing-Related Laws in Kuwait

Law No.	Description
2008/8	Imposes a tax on undeveloped residential lands exceeding 5000 square meters.
2008/9	Prohibits corporate investors from owning low-density residential lands.
2018	Electricity tariff increased from 2 Fils/kWh to 5 Fils/kWh, and water tariff increased from 0.8 KWD to 2 KWD per 1000 Gallons for investment residential units.
2023/118	Enables the Public Authority for Housing Welfare to establish housing development companies with up to 49% private sector ownership.
2023/126	Imposes an incremental tax on undeveloped low-density land exceeding 1500 sqm, starting at 10 KD/sqm and increasing annually until 100 KD/sqm; adjusts Law 2008/8. Defines undeveloped land as less than 50% developed and imposes restrictions on banking sector dealings with low-density residential properties.

In 2008, the legislature passed two laws: 2008/8 and 2008/9. Law 2008/9 aims to lessen residential property market concentration by forcing corporate investors to exit the low-density single-home residential market. Law 2008/8 imposes a tax on undeveloped residential lands exceeding 5,000 square meters.

In 2018, the electricity and water rates for investment residential properties increased relative to the low-density ones, potentially, making the low density properties market more attractive for investors.

In 2023, the legislature passed two housing-related laws: Law No. 118 and Law No. 126. Law 2023/126 imposes an incremental tax on undeveloped low-density land when total ownership exceeds 1,500 square meters. It is an adjustment to the previous 2008/8 law, which imposed a non-incremental tax. The new law's tax rate starts at 10 KWD per square meter and increases by 30 KWD/sqm yearly until it reaches 100 KWD/sqm. According to the law, undeveloped land is defined as land that is less than 50% developed. It also imposes some restrictions on the banking sector in dealing with low-density residential properties.

Law No. 118 aims to engage the private sector in developing residential cities. It enables the Public Authority for Housing Welfare to establish housing development companies where the private sector may own up to 49%.

The limited availability of data on Kuwait's housing market makes ABM a handy tool for assessing the impact of government policies on the Kuwaiti housing market. Agent-based models also provide a rich framework for exploring the potential effects of policies before they are enacted.

Until 2008, both corporate and individual investors could invest in (own and develop) both types of properties. In 2008, the government passed Law No. 9, which prohibits corporate investors from owning low-density residential land. The rationale was that reducing corporate investor participation in the low-density residential market would lower demand, thereby increasing housing affordability.

A key research question is whether such a law achieves its objective of making housing more affordable. Alfalah et al. (2023) measured housing affordability indices for Kuwait from 2004 to 2017 and found that, despite the law, housing affordability has worsened. However, one cannot determine the precise impact of the law on housing affordability solely by examining these indices. The law could have a positive, negative, or negligible effect. It is essential to isolate and control for the many other factors that could influence housing prices.

Prohibiting corporate investors from investing in the low-density residential land market might drive them to divert some funds to alternative investments. Many real estate alternative investment opportunities exist, such as investing in industrial, commercial, agricultural, and investment residential real estate properties. Hence, the demand for those alternative real-estate options would go upward, potentially driving their prices upward, ceteris paribus. This may, in turn, reduce their attractiveness to individual investors, increasing the relative attractiveness of low-density residential real estate properties. Hence, some individual investors may exit from the market where corporate investors are and enter the residential market, putting upward pressure on the prices of the residential, ceteris paribus.

Both corporate and individual investors' behavior affects their environment (markets), and the environment affects their behavior, making the market system complex. Agent-based modelling is a suitable tool to explore the dynamic effect of such a policy on residential and investment land markets. There are three main players in low-density residential lands: individual investors, corporate investors, and homeowners. Agent-based modelling allows for the study of the law's impact on the investor's behavior in isolation.

A simple model can be built. The model can consist of two types of agents, individual investors and corporate investors, and multiple markets: commercial, agricultural, industrial, residential investment, and low-density residential markets. Each type of agent behaves according to specific rules. The agents can be heterogeneous. For example, agents may differ in terms of their funds or wealth. Gilbert et al. (2009)'s model of the UK residential market can be used as a base for our situation in Kuwait. In their model, however, there is only one type of real estate property.

The properties are spread on a grid world and differ by their prices. There are three types of agents: buyers, sellers, and realtors, and a single market. In our situation, we have multiple markets where the corporate and individual investors can be sellers and buyers. Features of some previously discussed industrial organization models, such as market attractiveness evaluation and entry and exit decisions Dawid and Reimann (2005), can be incorporated.

Another interesting policy change that could potentially have impacted the residential market in Kuwait and is worth studying is the change in electricity and water tariffs. In 2018, the Ministry of Electricity and Water in Kuwait raised the rate for electricity and water for residential investment units from 2 Fils/kWh to 5 kWh and from 0.8 KWD to 2 KWD per 1000 Gallons, respectively, keeping the rates for the low-density units unchanged at 2 Fils/kWh, and 0.8 KWD per 1000 Gallons.

Potentially, such a policy may negatively impact the affordability of housing. For multiple reasons, the relative increase in electricity and water rates for the investment residential units could make the investment residential market less attractive for investors. First, while the Ministry of Electricity and Water provides electricity meters for each rental unit, it only provides a single water meter for the whole building. Thus, in many rental contracts, electricity and water costs are included with the rent. Second, investors cannot entirely pass the increase in tariff on to the renter by directly increasing rents. This is partly due to the law limiting investors in raising rents in the short term. Additionally, the elasticity of rental apartment demand limits how much could be passed on. Other markets, including the low-density residential market, might become more attractive. Thus, some investors may enter the low-density residential market, causing housing prices to increase, ceteris paribus.

A closely related policy that could have impacted not just housing prices but also the housing landscape in Kuwait is the heavy subsidy on electricity and water. Removing the subsidy can be a disruptive policy with a large potential impact. Such a change in policy can incentivize changes in other real estate-related laws and building codes that could potentially allow for more innovative designs and housing.

The potential interdependence between utility tariffs and the housing market appears to be understudied. The lack of regular and accurate utility data in Kuwait inhibits the possibility of any empirical studies in that area. Agent-based modelling can be used as a tool to explore such interdependence. Understanding the impact of such policy change may require a richer model incorporating features such as innovation, entry and exit decisions (Dawid & Reimann, 2005), and the construction sector (Mérő et al., 2023).

Recently, two housing-related laws have been passed: Law 2023/118 and 2023/126. Law 2023/126 imposes taxes on undeveloped residential properties, while Law 2023/118 aims to engage the private sector in developing residential cities. The high incremental tax rate imposed by law 2023/126 may incentivize the landowners to develop or sell their lands. Law 2023/118 may expedite the residential development projects, increasing the housing supply and potentially making housing more affordable. An empirical assessment of the impact of each law separately can be very challenging. Things can even get more complicated when considering the effect of the announcement of both statutes. This is evident in the impact of the announcement of monetary policies on asset prices (Gürkaynak et al., 2004). Agent-based modelling can provide a proper toolbox for understanding the potential effect of both laws.

Law 2023/118 is a first step towards engaging the private sector in developing housing solutions. Kuwaiti low-density residential areas lack a variety of housing products and are primarily dominated by single homes. For example, small townhouses represent a small share of the housing units in Kuwait. This is partly due to the building code, which heavily restricts the building of attached houses. However, it is possible to build small townhouses in investment residential lands. Anecdotal evidence from new residential investment areas, such as Hessah Al-Mubarak, shows that such houses are highly sought after. Other factors, such as location, could make them highly sought after. Nevertheless, we believe there is a large gap in the literature for investigating the desirability and demand of such houses and how a policy change that allows the development of small townhouses and other varieties of housing units in low-density residential affects the shape of the housing market landscape and the affordability of housing.

As land size shrinks, the price of land per square meter increases. The high land prices may incentivize landowners to divide their lots into smaller, more affordable lots. While the total land area in the market remains the same, the number of units will increase. The increase in the supply of residential units would affect the land prices, which would affect the landowner's decision to divide lots. Agent-based modelling is a suitable toolkit for modelling and understanding the dynamics of such a policy change.

The low supply of low-density residential land is a primary factor affecting housing affordability in Kuwait. The government, through the Public Authority for Housing Welfare (PAHW), is considered the leading supplier of housing. To this date, the private sector has played a limited role in the housing sector. The only exception is the Sabah Al Ahmad Sea City. While the most significant part of the Sabah Al Ahmad Sea City is designated as a low-density residential area, the lots are primarily developed for recreational use. While law 2023/118 aims to engage the private sector in developing housing projects, it largely restricts private developers to working only on projects under the Public Authority for Housing Welfare (PAHW). The private sector can be more engaged in the development of housing products if it is allowed to develop and sell units to anyone in the market, not just PAHW-qualified individuals.

There are many details and issues involved in allocating public lands to the private sector working in housing development in Kuwait. Let's simplify the situation and assume that the government will sell large lots to private sector developers to plan and develop into different types of low-density residential units. The main question would be how to set the price? One possible approach is to sell the lands through auctions. If the lands are to be auctioned, what format of auctions should be used? Auctions format can affect the market structure. For example, Dong and Sing (2016) show that first-price sealed-bid auctions result in a competitive real estate development market, while the English auction results in a monopoly.

Public land allocation for residential development through auctions has witnessed varying success. Some attempts show considerable issues, such as auctioned lands remaining undeveloped for long periods after the allocations (Lin & Cheng, 2016). Others show promising results (Caesar, 2016). Agent-based models can be used to explore the potential performance of different auction formats on the allocation of public lands. Additionally, they can provide a flexible framework for optimal land-use planning, which supplements public land allocation policies (Ligmann-Zielinska & Jankowski, 2010; Zhao et al., 2019).

Methodology

We aim to build an agent-based housing market model using the NetLogo language (Tisue & Wilensky, 2004). Our treatment will be as follows. First, we describe and define our model. Then, we explain how to implement it in NetLogo. After that, we show how the model can be analyzed using external statistical tools, such as R, and conduct some basic analysis illustrating some insights the model can provide.

We use our model to study the effect of the number of market speculators on housing prices and the effect of market efficiency, or the search cost, on housing price volatility. The first is motivated by some policymakers' belief in the potential negative effects of speculators on housing prices. The second is motivated by some interest in the literature in the effect of market efficiency and transaction costs on the volatility of prices. For example, Jones and Seguin (1997) conducts a quasi-experimental design-based study on the New York Stock Exchange market and finds that reducing transaction costs increases trading volume and decreases price volatility. Price volatility is widely seen as an indicator of market efficiency (Földvári & van Leeuwen, 2011). Other studies focused on the relationship between housing prices and market frictions. For example, Diaz and Jerez (2013) build a model that aims to understand the relationship between search frictions, price volatility, and trading delays. Caplin and Leahy (2011) model the relationship between liquidity, trading frictions, and housing prices. Yang (2020) provides a review and a transaction-based analysis of the speculation in the housing market price dynamics. In our paper, we aim to understand the relationship between market efficiency as designated by the search cost and price volatility using an agent-based simulation model.

Model Specification

Our model is a conceptual simplified representation of the housing market. Our objective is to use the model to illustrate the building process of agent-based models. We kept the model simple, yet rich enough to serve that purpose. Due to the limitation of data availability and the conceptual nature of the model, the model is not calibrated with market data. Parameter distributions were chosen based on a conceptual basis. Nevertheless, the calibration and validation of agent-based models is an important research issue that has attracted the attention of some researchers in the field (Guerini & Moneta, 2017; Gürcan et al., 2013).

The model consists of N heterogeneous agents or traders. The agents are endowed with wealth randomly drawn from the normal distribution. Agents can have income in a similar fashion to Gilbert et al. (2009). N_h of the agents are endowed with a house. The reservation price for these agents is drawn from a uniform distribution between 0.5 and 1 unit of price to create dispersion in real estate value estimates (Linneman, 1986). The houses are homogeneous. N_f agents are flippers, or speculators; they buy a house to resell it with a markup. The remaining $N - N_f$ agents will hold the house and will not be able to sell it for at least a period that is drawn from a random uniform distribution period between $Tsell_{min}$ and $Tsell_{max}$. Agents with a house, and that are eligible to sell it will attempt to sell the house. They will find a buyer with probability p_s. The p_s probability serves as a search cost parameter. In a more developed and efficient market, buyers spend less time in finding a potential seller (Malone & Rockart, 1991). We operationalize such market efficiency, characterized by the search cost, with such a probability parameter. Buyers will buy the house as long as their maximum willingness to pay is equal to or greater than the price and they are able to purchase the house. Non-flipper sellers who are unsuccessful in finding a potential buyer will reduce their prices by $N_{discount} \times 100$ percent. This assumption is based on studies on the relationship between initial listing prices, and price reduction (Knight, 2002). Flippers will only sell the houses at a price that is at least the purchase price with a markup. Prices, wealth, and income are normalized to 1.

Analysis

The model is typically analysed by simulating it and measuring some statistics. We will discuss and illustrate how to simulate our agent-based model using two tools: BehaviorSpace, and RNetLogo. BehaviorSpace is an integrated NetLogo tool that allows to simulate the model and calculate specific statistical measures. The tool can utilize the multi-core processors and run multiple simulations in parallel. RNetLogo (Thiele, 2014) is an R package that provides an interface to NetLogo within R.

RNetLogo interfaces NetLogo through Java, and thus the eJava package is required as well as Java 8 or higher. Although the RNetLogo package requires a NetLogo version 6 or higher, our testing reveals that the package suffers from some compatibility issues with some of the newer versions of NetLogo. For example, we were not able to load the model from R using version 6.2.1; however, we were able to start NetLogo from R and load the model manually through the graphical interface of NetLogo and run the model successfully. We have also tried to test the package with the most recent version of NetLogo, version 6.4.0, and noticed that there were some issues with starting NetLogo from R. It was not possible to start the model manually and run it from R.

Despite some of the compatibility issues in RNetLogo, the package facilitates reproducibility. There are many tools in R that facilitate reproducible research such as Sweave (Meredith & Racine, 2009) and more recently Quarto (Quarto, n.d.). By interfacing NetLogo from R, one would be able to integrate the manuscript of a research paper with its analysis into a single framework, which facilitates reproducibility, which is beyond the scope of our work.

Results

We analyze the model to explore two things. The first is the effect of market efficiency on price volatility. We operationalize market efficiency by introducing a probability parameter, denoted as the ‘ps’ parameter. The parameter represents the probability of buyers' ability to search for a seller. The second is the effect of the proportions of the speculators in the market on market price and its volatility.

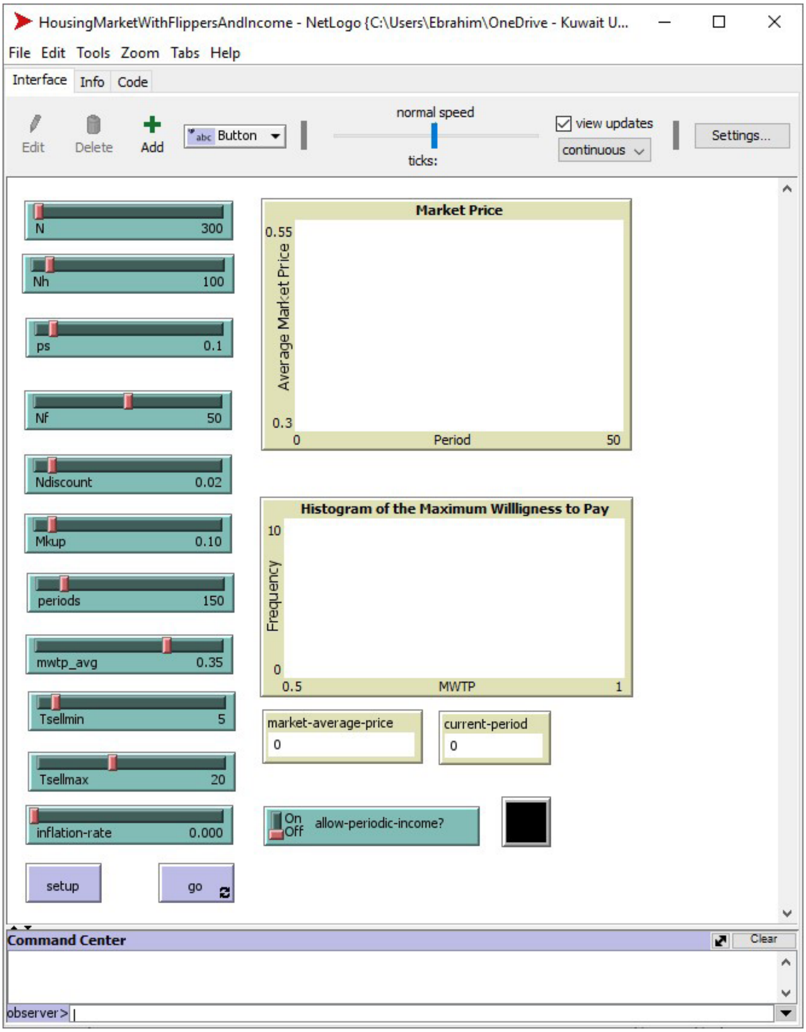

Figure 1: Netlogo Agent-Based Models Integrated Development Environment

The baseline values of the other parameters are shown in Figure 1. The empirical measurement of market efficiency is a challenging task (Földvári & van Leeuwen, 2011). Agent-based models, such as our model, provide an artificial laboratory to explore the effect of market efficiency on price volatility. Our results, as shown in Figure 2, suggest that the increase in market efficiency results in a decrease in the market price volatility. This finding is supported by some empirical works that attempted to explore the relationship between the two. For example, Földvári and van Leeuwen (2011) developed a methodological approach to measuring price volatility and showed that an increase in market efficiency is associated with a decrease in market price volatility.

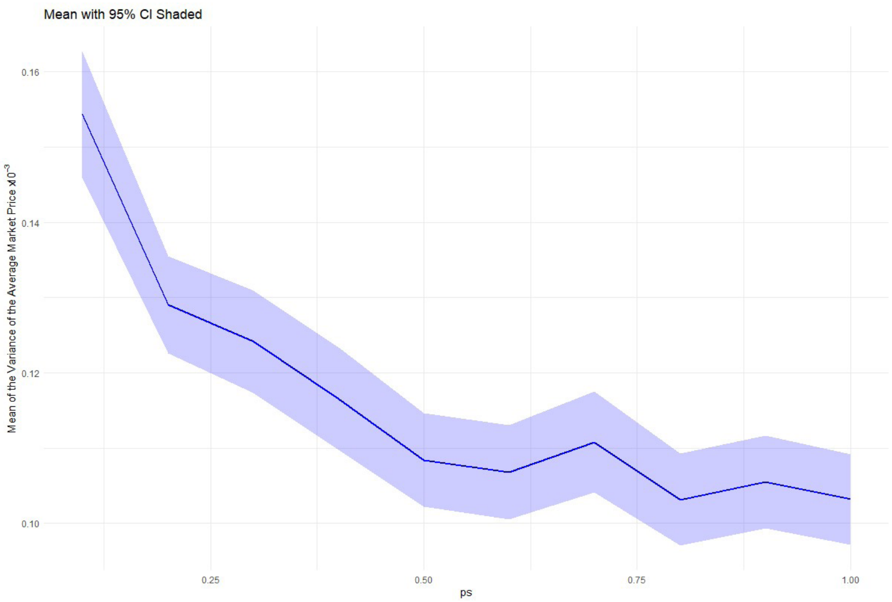

Figure 2: Effect of Market Efficiency (Ps) on Market Price Volatility

We further explore the effect of market flippers or speculative traders on market price. Figure 3 reveals that the larger the number of speculative traders, the lower the market price volatility is. However, the number of speculative traders appears to have no effect on the market average price, as shown on Figure 4.

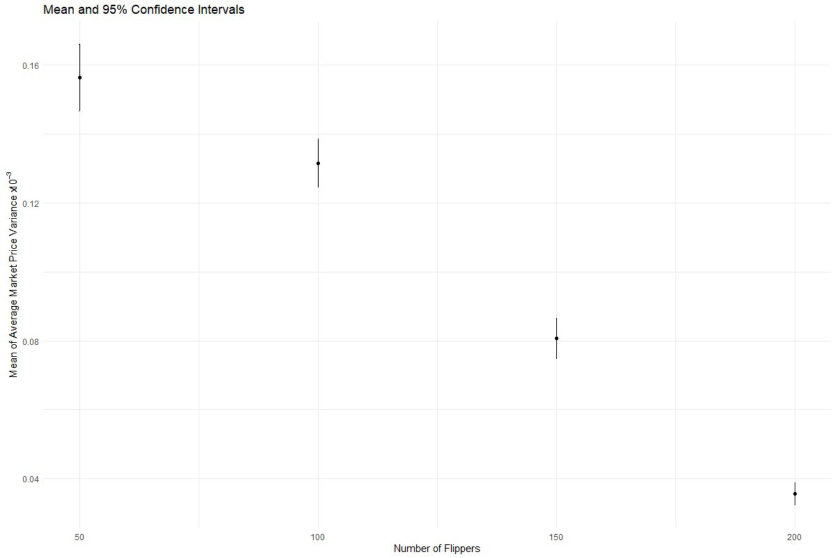

Figure 3: The Effect of the Number of Flippers on Market Price Volatility

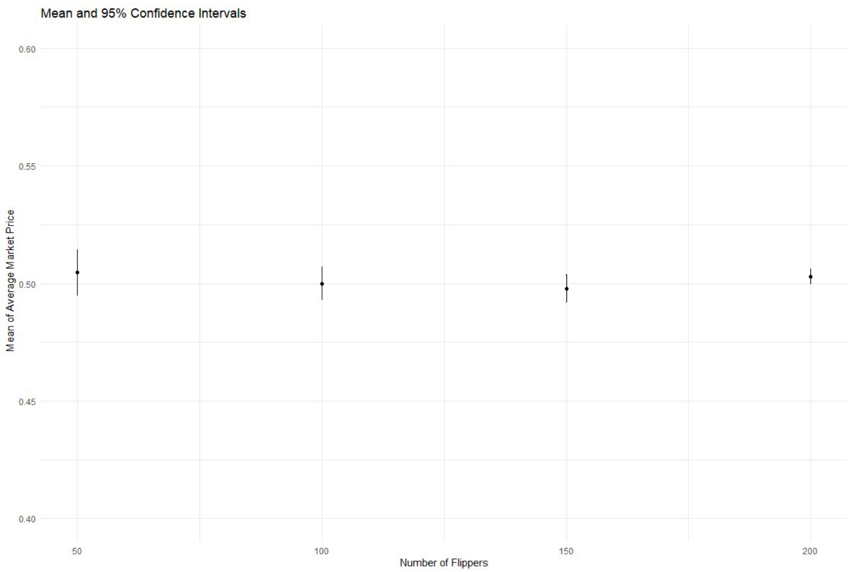

Figure 4: The Effect of the Number of Flippers on Market Price

Discussion

Agent-based models shall not be seen as an alternative to the pure mathematical modelling approach in economics. They should be seen as a supplementary approach to situations where mathematical modelling may not be handy or even possible. Such a situation can arise when rational expectation models may not be appropriate or when multiple equilibria are possible (Arthur, 2006). As discussed in Arthur (2006), ABM can provide insights on how multiple equilibria can evolve. It can also provide insight into how agents can adapt their expectations in deviation from the paradigm of rational expectations.

Although ABM models are being used in many fields, the limited use of the approach by economists is puzzling. It is also interesting that many agent-based economic model contributions come from researchers outside the field of economics, such as engineering and computer science. Looking at the literature, we can deduce that tractability is a major reason for that. Unlike applied scientists and engineers, economists historically tend to incline toward the tractability inherent in the mathematical modelling. In other words, they tend to favor a model that can be expressed and analyzed in a mathematical form over a simulation-based model, such as an agent-based model. Smith (2008) provides a detailed treatment of that aspect.

There is a large gap that ABM models can still fill in the economics, and business literature. For example, in the search literature, building a model that has searched in equilibrium is a main challenge. Agent-based models allow for deviation from the notion of equilibrium. Thus, one can build a model to examine agents' behavior and market prices off equilibrium. Additionally, they can be used to check the robustness of mathematical models to assumptions. Agent-based models have also been used as a complementary method to experimental IO (Duffy, 2006).

Agent-based models can be built for different purposes. They can be conceptual models for understanding specific behaviours or can be very sophisticated ones that aim to create an artificial replica of reality. The conceptual models can be very simple yet provide practical insights. Schelling's segregation model (Schelling, 1978) is an example of that. While his model is very abstract and simple, it provides useful insights into the racial segregation in the housing market. Our model is another example. The models by Axtell et al. (2014), Baptista et al.

(2016), and Evans et al. (2023) aim to replicate some real market features. Figure 5 illustrates the agent-based modeling process.

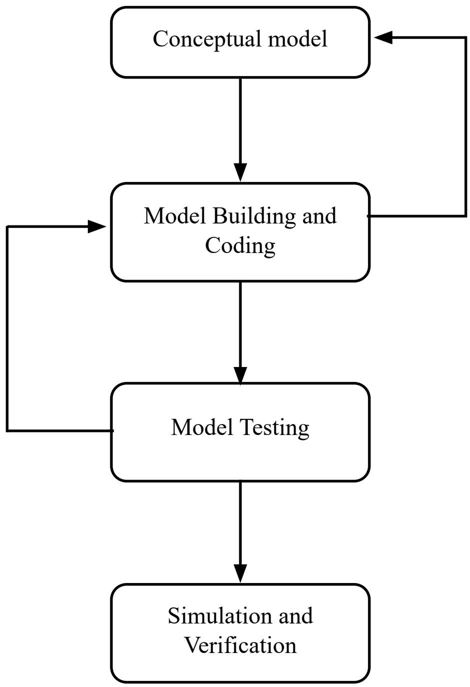

Figure 5: Agent-Based Model Building Process

Practical Implications

Our work has immense practical implications on policymaking in Kuwait. Market data on housing transactions in Kuwait are limited. Publicly available data lack important details such as precise locations. Additionally, details on some essential characteristics of houses may not even exist. Other data, such as historical data on utilities such as electricity and water consumption, are not recorded regularly, and the data available with service providers are likely to be very noisy. Such limitations make agent-based models an important tool for policy-making in Kuwait.

Using the model developed, we have shown how agent-based models can provide some market insights. For example, we have shown that increasing market efficiency results in a decrease in price volatility. Additionally, we have shown that market speculators or flippers can have a positive effect on smoothing market price volatility. Such insights can be very beneficial for policymakers and market authorities.

Our finding suggests that the policymaker should pursue policies toward decreasing search costs and increasing housing market efficiency. For example, this can be achieved by taking steps toward policies that facilitate the establishment of a multiple listing system, where realtors can share their listings across multiple platforms, which can significantly decrease the search cost, and hence price volatility. Additionally, our finding suggests that caution should be taken toward any policy affecting the speculators in the market. Agent-based models can provide an environment for studying complex behavioural change and its effect on the market outcome in response to policy changes, which can supplement other types of studies' findings.

Conclusion

An agent-based model is a handy and flexible modeling tool to get insights and answers to problems where data is limited. It can also be useful in conducting a supplementary analysis to both empirical and experimental studies. We can summarize the agent-based modelling process as follows:

1. Design a model conceptually. The design step includes specifying the types, number of agents, and their roles as well as the environment setup. For example, in our model, we have two types of agents interacting in a single market. Each type of agent behaves according to a set of rules.
2. The model is translated into a computer code using an agent-based modeling tool such as NetLogo. This step reveals any necessary missing assumptions or incomplete parts of the conceptual model that require adjustment.
3. Test the coded model to ensure that its parts behave as designed.
4. Simulate and verify the model. This step involves a calculation of statistics of some of the model variables. For example, in our model, we were interested in the variance and the mean of the housing prices and their relationship with search cost, and number of speculators.

Agent-based models facilitate building models for both normative and positive economic analyses. Economists use mathematical and statistical models to either understand the effect of a policy change or propose a policy that aims to achieve specific outcomes. Mathematical models suffer from tractability. As more variables are added, they become more challenging to solve, both in closed form and numerically. Hence, their analysis is limited to a few variables, while statistical models rely on data availability. The simulations-based nature of agent-based models expands the possibilities of normative economics even with limited data availability. It allows economists to estimate and test policies for large-dimensional models.

Most policy-oriented ABM studies are scenario-based. In other words, they decide on the best actions or policies to take based on the simulation of a limited set of proposed policies. Recent dynamic optimization algorithms, such as reinforcement learning optimization algorithms (Sutton & Barto, 2020), expand the capacity of ABM policy-making studies. Rather than having a few proposed policies to decide on, it is possible to optimize parametrized policies.

Reinforcement learning algorithms have been used in different applications in the Agent-Based Modelling literature compared to the one we refer to. They have been applied to equip agents with learning capacity rather than to optimize a policy that could affect agents. The former can be seen as a special case of the latter, where the government or the policymaker is a learning agent in the environment.

In our paper, we aimed to bridge the gap in the literature by providing an overview of the application of agent-based models in the industrial organization literature in general, and a review of the issues in the Kuwaiti housing market structure addressing the potential use of agent-based models and features of some models in the literature in understanding the effect of policy changes on the structure of the market and the market prices. Furthermore, we develop a conceptual extensible market model and illustrate the basics of building and analyzing the model in NetLogo and R language.

References

Alfalah, A., Stevenson, S., Heinig, S., & D'Arcy, E. (2023). Housing affordability in a resource rich economy: The case of Kuwait. *International Journal of Housing Markets and Analysis, 16*(2), 336–353. https://doi.org/10.1108/IJHMA-02-2022-0020

Alghais, N., & Pullar, D. (2018). Modelling future impacts of urban development in Kuwait with the use of ABM and GIS. *Transactions in GIS, 22*(1), 20–42. https://doi.org/10.1111/tgis.12293

Andreoni, J., & Miller, J. H. (1995). Auctions with artificial adaptive agents. *Games and Economic Behavior, 10*(1), 39–64. https://doi.org/10.1006/game.1995.1024

AnyLogic. (2023). *Simulation modeling software tools solutions for business*. Retrieved September 11, 2023, from https://www.anylogic.com/

Araúzo, J. A., Villafáñez, F. A., García, D. P., Pajares, J., & Pavón, J. (2018). Agent-based modelling and simulation of an auction market for airport slots allocation. In J. Bajo et al. (Eds.), *Highlights of practical applications of agents, multi-agent systems, and complexity: The PAAMS collection* (Vol. 887, pp. 421–432). Springer. https://doi.org/10.1007/978-3-319-94779-2_39

Arthur, W. B. (2006). Out-of-equilibrium economics and agent-based modeling. In L. Tesfatsion & K. L. Judd (Eds.), *Handbook of computational economics* (Vol. 2, pp. 1551–1564). Elsevier. https://doi.org/10.1016/S1574-0021(05)02032-0

Axelrod, R., & Tesfatsion, L. (2006). A guide for newcomers to agent-based modeling in the social sciences. In L. Tesfatsion & K. L. Judd (Eds.), *Handbook of computational economics* (Vol. 2, pp. 1647–1659). Elsevier. https://doi.org/10.1016/S1574-0021(05)02044-7

Axtell, R., Farmer, J. D., Geanakoplos, J. D., Howitt, P., Carrella, E., Conlee, B., Goldstein, J., Hendrey, M., Kalikman, P., Masad, D., Palmer, N., & Yang, C.-Y. (2014). An agent-based model of the housing market bubble in metropolitan Washington D.C. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4710928

Baptista, R., Hinterschweiger, M., Low, K., & Uluc, A. (2016). Macroprudential policy in an agent-based model of the UK housing market. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2850414

Borsato, A., & Lorentz, A. (2023). Data production and the coevolving AI trajectories: An attempted evolutionary model. *Journal of Evolutionary Economics, 33*, 1427–1472. https://doi.org/10.1007/s00191-023-00837-3

Box, G. E. P. (1976). Science and statistics. *Journal of the American Statistical Association, 71*(356), 791–799. https://doi.org/10.1080/01621459.1976.10480949

Boyer, C. N., & Brorsen, B. W. (2014). Implications of a reserve price in an agent-based common-value auction. *Computational Economics, 43*(1), 33–51. https://doi.org/10.1007/s10614-013-9413-8

Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., & Zaremba, W. (2016). *OpenAI Gym*. arXiv. https://arxiv.org/abs/1606.01540

Caesar, C. (2016). Municipal land allocations: Integrating planning and selection of developers while transferring public land for housing in Sweden. *Journal of Housing and the Built Environment, 31*(2), 257–275. https://doi.org/10.1007/s10901-015-9457-2

Cantner, U., & Pyka, A. (1998). Absorbing technological spillovers: Simulations in an evolutionary framework. *Industrial and Corporate Change, 7*(2), 369–394. https://doi.org/10.1093/icc/7.2.369

Caplin, A., & Leahy, J. (2011). Trading frictions and house price dynamics. *Journal of Money, Credit and Banking, 43*(s2), 283–303. https://doi.org/10.1111/j.1538-4616.2011.00436.x

Catullo, E. (2013). An agent-based model of monopolistic competition in international trade with emerging firm heterogeneity. *Journal of Artificial Societies and Social Simulation, 16*(2), 7. https://doi.org/10.18564/jasss.2155

Dawid, H., & Reimann, M. (2005). Evaluating market attractiveness: Individual incentives versus industry profitability. *Computational Economics, 24*, 321–355. https://doi.org/10.1007/s10614-005-6158-z

Dawid, H., & Neugart, M. (2023). Effects of technological change and automation on industry structure and (wage-)inequality: Insights from a dynamic task-based model. *Journal of Evolutionary Economics, 33*, 35–63. https://doi.org/10.1007/s00191-022-00803-5

Díaz, A., & Jerez, B. (2013). House prices, sales, and time on the market: A search-theoretic framework. *International Economic Review, 54*(3), 837–872. https://doi.org/10.1111/iere.12019

Dong, Z., & Sing, T. F. (2016). How do land auction formats influence the market structure and aggregate surplus of real estate development? *Real Estate Economics, 44*(3), 691–725. https://doi.org/10.1111/1540-6229.12117

Duffy, J. (2006). Agent-based models and human subject experiments. In L. Tesfatsion & K. L. Judd (Eds.), *Handbook of computational economics* (Vol. 2, pp. 949–1011). Elsevier. https://doi.org/10.1016/S1574-0021(05)02019-8

Esmaeili Avval, A., Dehghanian, F., & Pirayesh, M. (2022). Auction design for the allocation of carbon emission allowances to supply chains via multi-agent-based model and Q-learning. *Computational and Applied Mathematics, 41,* 170. https://doi.org/10.1007/s40314-022-01868-5

Evans, B. P., Glavatskiy, K., Harré, M. S., & Prokopenko, M. (2023). The impact of social influence in Australian real estate: Market forecasting with a spatial agent-based model. *Journal of Economic Interaction and Coordination, 18,* 5–57. https://doi.org/10.1007/s11403-021-00324-7

Fabretti, A., & Herzel, S. (2017). An agent-based model for a double auction with convex incentives. *Journal of Artificial Societies and Social Simulation, 20*(1), 7. https://doi.org/10.18564/jasss.3246

Fackler, P. L., & Goodwin, B. K. (2001). Spatial price analysis. In B. L. Gardner & G. C. Rausser (Eds.), *Handbook of agricultural economics* (Vol. 1, Part B, pp. 971–1024). Elsevier. https://doi.org/10.1016/S1574-0072(01)10025-3

Földvári, P., & van Leeuwen, B. (2011). What can price volatility tell us about market efficiency? Conditional heteroscedasticity in historical commodity price series. *Cliometrica, 5,* 165–186. https://doi.org/10.1007/s11698-010-0055-y

Gardner, M. (1970). Mathematical games. *Scientific American, 223*(4), 120–123. https://doi.org/10.1038/scientificamerican1070-120

Gilbert, N., Hawksworth, J. C., & Swinney, P. A. (2009). An agent-based model of the English housing market. *AAAI Spring Symposium - Technical Report, SS-09-09*, 30–35. An Agent-Based Model of the English Housing Market – AAAI.

Guerini, M., & Moneta, A. (2017). A method for agent-based models validation. *Journal of Economic Dynamics and Control, 82*(42), 125–141. https://doi.org/10.1016/j.jedc.2017.06.001

Gunaratne, C., & Garibay, I. (2021). NL4Py: Agent-based modeling in Python with parallelizable NetLogo workspaces. *SoftwareX, 16*, 100801. https://doi.org/10.1016/j.softx.2021.100801

Gürcan, Ö., Dikenelli, O., & Bernon, C. (2013). A generic testing framework for agent-based simulation models. *Journal of Simulation, 7*(3), 183–201. https://doi.org/10.1057/jos.2012.26

Gürkaynak, R. S., Sack, B. P., & Swanson, E. T. (2004). Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *SSRN Electronic Journal*. https://dx.doi.org/10.2139/ssrn.633281

Hailu, A., & Thoyer, S. (2007). Designing multi-unit multiple bid auctions: An agent-based computational model of uniform, discriminatory and generalised Vickrey auctions. *Economic Record, 83*(S1), 57–73. https://doi.org/10.1111/j.1475-4932.2007.00410.x

Hax, A. C., & Majluf, N. S. (1983). The use of the industry attractiveness-business strength matrix in strategic planning. *Interfaces, 13*(2), 54–71. https://doi.org/10.1287/inte.13.2.54

Heath, B. L., & Hill, R. R. (2008). The early history of agent-based modeling. *IISE Annual Conference Proceedings*, 971–976. Retrieved from https://www.proquest.com/scholarly-journals/early-history-agent-based-modeling/docview/192465049/se-2

Hendricks, P. (2016). *Gym: Provides access to the OpenAI Gym API* (R package). GitHub. https://github.com/paulhendricks/gym-R

Hjorth, A., Head, B., & Wilensky, U. (2020). Levelspace: A NetLogo extension for multi-level agent-based modeling. *Journal of Artificial Societies and Social Simulation*, *23*(1), 4. https://doi.org/10.18564/jasss.4130

Jones, C. M., & Seguin, P. J. (1997). Transaction costs and price volatility: Evidence from commission deregulation. *The American Economic Review, 87*(4), 728–737. https://www.jstor.org/stable/2951371

Kagel, J. H., & Dyer, D. (1988). Learning in common value auctions. In R. Tietz, W. Albers, & R. Selten (Eds.), *Bounded rational behavior in experimental games and markets* (Vol. 314, pp. 294–318). Springer. https://doi.org/10.1007/978-3-642-48356-1_14

Knight, J. R. (2002). Listing price, time on market, and ultimate selling price: Causes and effects of listing price changes. *Real Estate Economics, 30*(2), 213–237. https://doi.org/10.1111/1540-6229.00038

Ligmann-Zielinska, A., & Jankowski, P. (2010). Exploring normative scenarios of land use development decisions with an agent-based simulation laboratory. *Computers, Environment and Urban Systems, 34*(5), 409–423. https://doi.org/10.1016/j.compenvurbsys.2010.05.005

Lin, T. C., & Cheng, Y. T. (2016). The missing public interest in land: Auctions of public land in Taipei City. *Issues and Studies, 52*(4), 1–21. https://doi.org/10.1142/S1013251116400038

Linneman, P. (1986). An empirical test of the efficiency of the housing market. *Journal of Urban Economics, 20*(2), 140–154. https://doi.org/10.1016/0094-1190(86)90003-3

Magliocca, N., Safirova, E., McConnell, V., & Walls, M. (2011). An economic agent-based model of coupled housing and land markets (CHALMS). *Computers, Environment and Urban Systems, 35*(3), 183–191. https://doi.org/10.1016/j.compenvurbsys.2011.01.002

Malone, T. W., & Rockart, J. F. (1991). Computers, networks and the corporation. *Scientific American, 265*(3), 128–136. https://doi.org/10.1038/scientificamerican0991-128

Meredith, E., & Racine, J. S. (2009). Towards reproducible econometric research: The Sweave framework. *Journal of Applied Econometrics, 24*(2), 366–374. https://doi.org/10.1002/jae.1030

Mérő, B., Borsos, A., Hosszú, Z., Oláh, Z., & Vágó, N. (2023). A high-resolution, data-driven agent-based model of the housing market. *Journal of Economic Dynamics and Control, 155*, 104738. https://doi.org/10.1016/j.jedc.2023.104738

Nelson, R. R., & Winter, S. G. (1985). *An evolutionary theory of economic change.* Belknap Press of Harvard University Press.

Noe, T. H., Rebello, M., & Wang, J. (2012). Learning to bid: The design of auctions under uncertainty and adaptation. *Games and Economic Behavior, 74*(2), 620–636. https://doi.org/10.1016/j.geb.2011.08.005

Ottino-Loffler, B., Stonedahl, F., Veetil, V. P., & Wilensky, U. (2017). *Spatial competition with interacting agents*. GMU Working Paper in Economics No. 15–62. https://dx.doi.org/10.2139/ssrn.2697263

Paldam, M. (2021). Methods used in economic research: An empirical study of trends and levels. *Economics, 15*(1), 28–42. https://doi.org/10.1515/econ-2021-0003

Pangallo, M., Nadal, J.-P., & Vignes, A. (2019). Residential income segregation: A behavioral model of the housing market. *Journal of Economic Behavior & Organization, 159*, 15–35. https://doi.org/10.1016/j.jebo.2019.01.010

Quarto. (n.d.). *An open-source scientific and technical publishing system.* https://quarto.org

Rahimiyan, M., & Rajabi Mashhadi, H. (2010). Evaluating the efficiency of divestiture policy in promoting competitiveness using an analytical method and agent-based computational economics. *Energy Policy, 38*(3), 1588–1595. https://doi.org/10.1016/j.enpol.2009.11.043

Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. *SIGGRAPH Computer Graphics, 21*(4), 25–34. https://doi.org/10.1145/37402.37406

Sanchez-Cartas, J. M. (2018). Agent-based models and industrial organization theory: A price-competition algorithm for agent-based models based on game theory. *Complex Adaptive Systems Modeling, 6*(2). https://doi.org/10.1186/s40294-018-0053-7

Schelling, T. C. (1978). *Micromotives and macrobehavior.* W. W. Norton & Company.

Silverberg, G., & Verspagen, B. (1994). Collective learning, innovation and growth in a boundedly rational, evolutionary world. *Journal of Evolutionary Economics, 4*(3), 207–226.

Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society, 106*(6), 467–482. https://www.jstor.org/stable/985254

Smith, P. (2008). *New perspectives on realism, tractability, and complexity in economics.* MPRA Paper 10899. University Library of Munich, Germany.

Sutton, R. S., & Barto, A. G. (2020). *Reinforcement learning: An introduction* (2nd ed.). MIT Press. Retrieved from http://incompleteideas.net/book/RLbook2020.pdf

Thiele, J. C. (2014). R marries NetLogo: Introduction to the RNetLogo package. *Journal of Statistical Software, 58*(2), 1–41. https://doi.org/10.18637/jss.v058.i02

Thiele, J. C. (n.d.). *Parallel processing with the RNetLogo package.*

Tseng, J.-J., Lin, C.-H., Lin, C.-T., Wang, S.-C., & Li, S.-P. (2010). Statistical properties of agent-based models in markets with continuous double auction mechanism. *Physica A: Statistical Mechanics and its Applications, 389*(8), 1699–1707. https://doi.org/10.1016/j.physa.2009.12.034

Tisue, S., & Wilensky, U. (2004). *NetLogo: Design and implementation of a multi-agent modeling environment.* Center for Connected Learning and Computer-Based Modeling, Northwestern University. https://ccl.northwestern.edu/papers/2004/netlogo-swarmfest2004.pdf

van Leeuwen, E., & Lijesen, M. (2016). Agents playing Hotelling's game: An agent-based approach to a game-theoretic model. *Annals of Regional Science, 57*(3), 393–411. https://doi.org/10.1007/s00168-015-0711-z

Wilensky, U. (2023). *NetLogo user manual (Version 6.3.0).* https://ccl.northwestern.edu/netlogo/docs/

Yang, Y. (2020). *Real estate price dynamics, property speculation, and housing price volatility: A study of the Auckland housing market*. [Master's thesis]. University of Auckland. https://hdl.handle.net/2292/56478

Zhang, L., Levinson, D., & Zhu, S. (2008). Agent-based model of price competition, capacity choice, and product differentiation on congested networks. *Journal of Transport Economics and Policy, 42*(3), 435–461. https://www.jstor.org/stable/20466758

Zhao, X., Ma, X., Tang, W., & Liu, D. (2019). An adaptive agent-based optimization model for spatial planning: A case study of Anyue County, China. *Sustainable Cities and Society, 51*, 101733. https://doi.org/10.1016/j.scs.2019.101733

Appendix

Agent-Based Modelling Tools

This part provides a brief overview of the available agent-based modelling toolboxes and packages. We can categorize the tools into three categories. The first is general simulation tools, combining multiple modelling approaches, such as system dynamics, discrete events, and agent-based models. The second category is tools that are primarily oriented toward agent-based models. The third focuses on the agent-based packages available for programming languages such as R, and Python

While we aim to discuss commercial, free, and open-source tools and software, we tend to focus more on open-source and free software. We aim to provide a brief overview of the available tools. The overview will compare the different tools, highlighting the pros and cons of each.

One widely used agent-based modeling tool is NetLogo (Wilensky, 2023). NetLogo was developed in 1999. It is based on StarLogo, an agent-based modelling tool developed by MIT Media Lab in 1989 (Wilensky, 2023). Both NetLogo and StarLogo are open source. However, it should be noted that the open-source version of the StarLogo is known as Open StarLogo. While StarLogo is more commonly used in education, NetLogo is used in education and research (Wilensky, 2023).

NetLogo's main advantages are its simplicity and extensibility. The models are developed using the simple NetLogo language. A basic model consists of agents, procedures, and variables. There are four types of agents. The first are patches, which make up the world of the model. The second are turtles, which move around the patches. The third are links, which connect turtles. The last agent is the observer, who observes and instructs the other agents. NetLogo is very extensible. R, Python, and other tools can be used to develop extensions to it. Additionally, there are packages that allow interfacing and embedding NetLogo models in R (Thiele, 2014) and Python (Gunaratne & Garibay, 2021), which allow access to a massive set of statistical and machine learning tools. It also allows more flexible multi-system modeling through its LevelSpace extension (Hjorth et al., 2020).

AnyLogic (2023) is multi-approach software for building discrete event, system dynamics, and agent-based models. It is commercial software with a free personal learning edition. The software has been used in academia and large corporations. One main advantage is that the models can be built using both graphical and code-based frameworks. It is also available for multiple operating systems.

There are very few Agent-Based Modelling packages in R. The ABM package provides a flexible framework for building and simulating agent-based models. The package can handle millions of agents and simulate the models in continuous time. AgentSim is another package. The package appears to be in its inactive experimental stage. The gym-R package (Hendricks, 2016) provides an interface to the Open AI Gym toolkit (Brockman et al., 2016). The Open AI Gym toolkit has been developed as a Python package to provide a framework for testing reinforcement learning algorithms rather than for developing agent-based models. However, the toolkit can be used to build Agent-Based Models.

NetLogo and Model Building Primer

Figure 6 shows the NetLogo Integrated Development Environment (IDE). The IDE has four main parts. The first is the interface. The interface is where the modeler designs the graphical interface of the model. Buttons, input fields, sliders, menus, output fields, and plots can be added to the interface to facilitate model parameter settings and output observations. For example, in our model, we have eleven sliders, two buttons, one switch, two plots, and two output fields. The interface components can be added using the add button. Each component can be configured in the interface by right-clicking on the component and choosing the edit option. The names of the sliders will be used as global variable names, which are case-insensitive. The setup button initializes the model, and the go button simulates the model. The second part is the info tab, which contains the documentation of the model. The third is the code tab, which contains the model code. The fourth is the command center. The command centre can be very useful in debugging and testing stage.

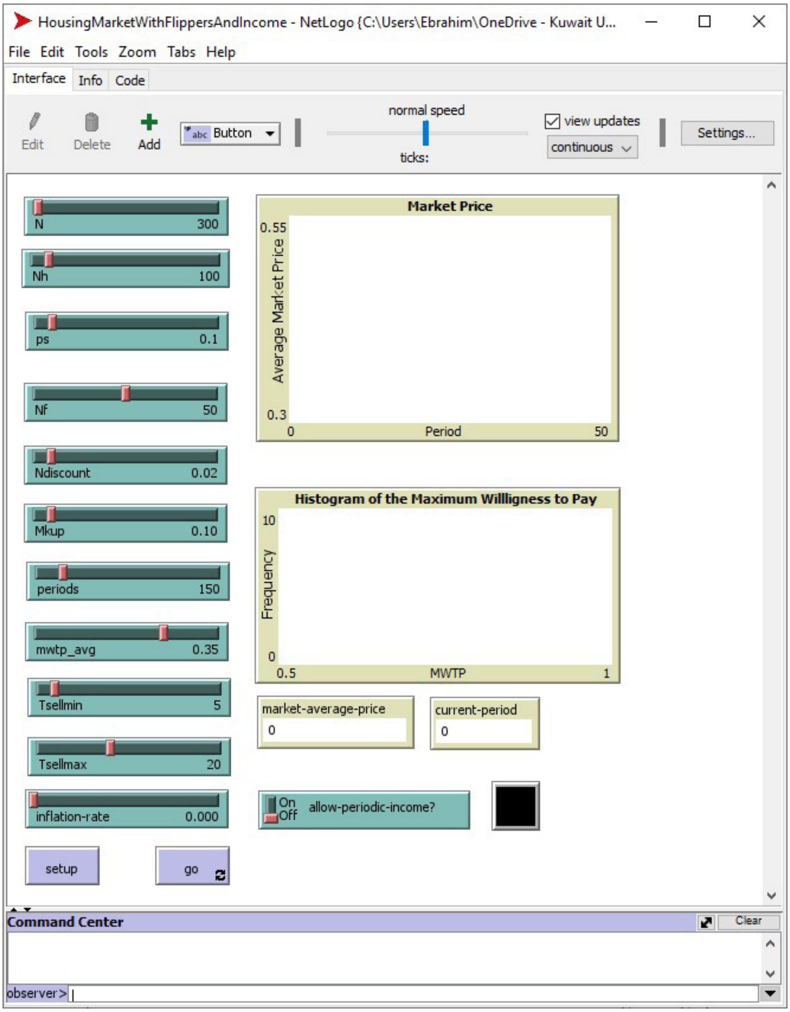

Figure 6: Netlogo Agent-Based Models Integrated Development Environment

The interface is primarily used for the model's initial experimentation. Not all model parameters must be defined within it; some can be defined within the code. Studies based on simulation models, such as agent-based models, require a large number of replications in order to get a more precise conclusion. One can do this either by using the NetLogo's BehaviorSpace tool or by interfacing the model with an external programming tool such as R-language. We will first explain the main parts of the code of our model and then illustrate how those tools can be used to analyse the model.

The code begins with definitions of agent types and variables. In our model, we have one type of agents: traders. The traders can be long-term homeowners or flippers. We can define the type of agent using the breed command as follows:

```
breed [traders trader]
```

Global variables can be defined as follows:

```
globals [
  current-period
  market-average-price
  transaction-prices]
```

The current-period is a clearer name for the default global variables that track the current period which is “ticks”. The market-average-price is the average price of the transactions at each period. The 'transaction-prices' is a list variable that records the prices of all completed transactions at each period.

Additionally, we have traders' specific variables. The traders' specific variables can be defined as follows:

```
traders-own [
  role
  purchase-price
  periodic-income
  purchase-period
  markup
  sell-after-period
  wealth
  mwtp
  has-house?
  reservation-price
]
```

The role is used to assign a role for the trader: a long-term homeowner or a flipper. The purchase-price records the most recent transaction price for each trader. The periodic-income is the trader earned income per period. The purchase-period records the period of the transaction. The sell-after-period records the number of periods after the purchase period at which the long-term homeowner would be able to sell the house. The wealth is the endowed wealth of the trader. The mwtp records the maximum willingness to pay for a house for each trader. A buyer will only buy a house if the seller's offer price is less than or equal to the maximum willingness to pay and the buyer can afford it. The has-house? is a Boolean variable that designates whether the trader owns a house (a potential seller) or not (a potential buyer). The reservation-price records the minimum price the long-term homeowner seller would accept to sell.

In NetLogo, the setup procedure consists of all the model initialization statements as follows:

```
to setup
  clear-all
  set market-average-price 0.5
  set transaction-prices []

  create-traders N [
     set wealth random-normal 1.2 0.2 ; Normal distribution, mean = 1, std = 0.2
    set has-house? false
   set mwtp mwtp_avg + random-float 0.5 ; Random value between mwtp_avg and 1

    ifelse allow-periodic-income?
    [set periodic-income random-gamma 0.1 1]
    [set periodic-income 0]
  ]

  ; Assign traders roles
  let flippers n-of Nar traders
  ask flippers [
    set role "flipper"
    set markup Mkup        ; flipper's markup percentage
    set purchase-price 0  ; Will be updated when house is purchased
  ]
  ask traders with [role != "flipper"] [
    set role "longhome-owner"
    set sell-after-period random (Tsellmax - Tsellmin + 1) + Tsellmin
  ]
```

```
  assign-houses
 reset-ticks
end
```

The setup procedure initializes the global variables: the market average price and transaction prices list; it creates N traders and initialize their variables. For example, the traders' wealth follows a normal distribution with mean 1.2 and standard deviation 0.2. Additionally, the role of each trader is assigned, such that N_f of them are chosen to be flippers, and N_h of the traders are endowed with a house by calling assign-houses procedure. The assign procedure is as follows:

```
to assign-houses
  let house-owners n-of Nh traders
  ask house-owners [
    set has-house? true
    set reservation-price mwtp
  ]
End
```

The reservation-price is set to equal the maximum willingness to pay. Once the model is initialized, it can be simulated by calling the "go" function. The "go" function in our model is as follows:

```
to go
  if ticks >= periods [ stop ]
  set transaction-prices []
  ask traders with [has-house?] [
    attempt-sale
  ]

  update-market-average-price
  ask traders [
      set wealth wealth + periodic-income
      set mwtp mwtp + mwtp * inflation-rate
  ]
  set current-period ticks
  tick
end
```

The simulation, as represented in the 'go' function, first reset the transaction-prices list variable, and then ask all traders with houses to attempt selling their houses. This is achieved by calling the procedure: attempt-sale. Traders who are long-term homeowners will be able to sell their homes if they satisfy the minimum holding requirement. Flippers can sell their houses at any period as long as they sell it for profit. Once the trading is complete, the market average price is calculated using the transaction prices for the current period by calling the update-market-average-price procedure. Traders' wealth is then updated by their per-period earned income. Traders also updated their maximum willingness to pay for houses if there is inflation. The simulation is then proceeded to the next period by calling the "tick" command. The attempt-sale function is as follows:

```
to attempt-sale
  ; Skip selling if the trader is a longhome-owner and hasn't reached the sell-after-period
  if role = "longhome-owner" and (current-period - purchase-period) < sell-after-period [
    stop
  ]

  ; Find potential buyers
  let buyers traders with [(not has-house?) and (wealth > mwtp) ]
  let successful? false  ; Track if a successful transaction occurs
  ; Determine the minimum price the seller will accept
  let min-price reservation-price
  if role = "flipper" [
    set min-price purchase-price * (1 + markup )
  ]

  ; Each buyer interacts with the seller
  ask buyers [
  if not successful? and random-float 1 < ps [
    let offer mwtp
    if offer >= min-price [
      ; Buyer updates
      set has-house? true         ;; Buyer gains ownership of the house
wealth)
      set wealth wealth - offer    ;; Buyer pays the seller
wealth)
```

```
        set reservation-price offer  ; Update buyer's reservation price

        ; Track purchase period for longhome-owners
        if role = "longhome-owner" [
          set purchase-period current-period
        ]
        ; Update purchase price for flippers
        if role = "flipper" [
          set purchase-price offer
        ]

        ; Seller updates
        ask myself [
          set has-house? False ; Seller no longer owns a house
wealth)
          set wealth wealth + offer   ; Seller receives payment
        ]

        ;; Mark the transaction as successful
        set successful? true
      ]
; Record the transaction price
      set transaction-prices lput offer transaction-prices
    ]

  ]
```

Model Simulation

In what follows, we will explain and illustrate the basic process of interfacing NetLogo in R with some code snippets. The first step is to install Java 8 JDK, rJava and RNetLogo package. Once installed and loaded in R, one needs to first start NetLogo from R and that is by calling the function:

NLStart(NetLogoPath, gui = TRUE,nl.jarname = "netlogo-6.2.1.jar"),

where NetLogoPath is the location of the NetLogo application in the drive, and nl.jarname designates the version of the NetLogo. As we have mentioned, we need to start NetLogo with GUI because of some version compatibility issue in loading NetLogo models from R. Ideally, once we start NetLogo we can load the model by calling the function

NLLoadModel(modelPath),

where the modelPath contains the location of the model in the drive. However, while the documentation of RNetLogo states the requirement of NetLogo version 6 or greater, the NLLoadModel has some issues with version 6.2.1. In that situation, one can load the model from the GUI of NetLogo once started. Hence, the GUI option in the NLStart function should be set to TRUE.

Once NetLogo is started, and the model is loaded, NetLogo commands can be executed by calling the function:

NLCommand("NetLogo command")

For example, we can call the setup function as follows

NLCommand("setup")

Variables' values can be retrieved by calling the NLReport function as follows

VariableValue <- NLReport("name of the variable")

Thiele (n.d.) explains how to simulate a NetLogo model in R by utilizing multi-core processors using the Parallel package.

BehaviourSpace is an alternative tool for simulating NetLogo model. The tool is integrated with NetLogo, and can be accessed from the tools menu. Figure 7 shows the simulation or experiment setup window. The tool simulates the model for every combination of variables values as listed in the "Vary variables..." box, and it calculates the required measures according to the commands listed in the "Measure..." box. For example, we can simulate our model for two values for the 'ps' variable, report the market-average-price for each simulated step, and replicate the simulation ten times, by setting up the simulation as shown in Figure 7. The simulation results are to be exported as a spreadsheet or CSV file. The BehaviorSpace tool can utilize multicore processors. The number of cores used when the simulation or the experiment is run can be specified when running the simulation.

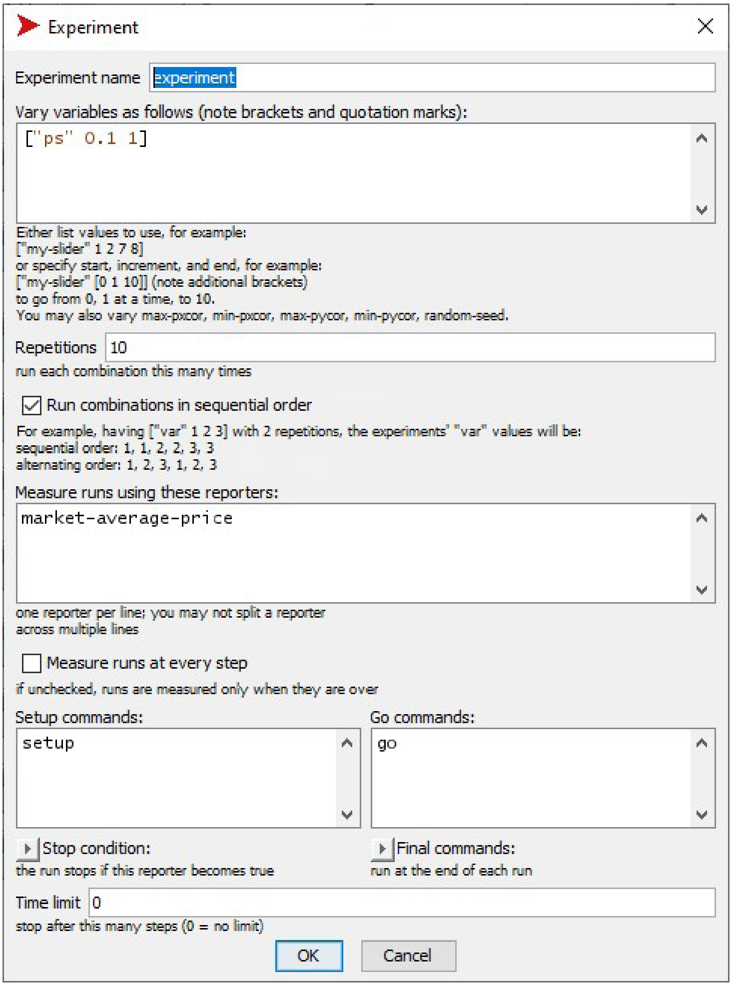

Figure 7: Behaviorspace Simulation Setup Window

Installation and Troubleshooting

NetLogo website provides a very detailed documentation on the installation, loading, and running models. The development environment of NetLogo is very user-friendly. However, interfacing NetLogo with R can be a daunting task, as one may face some compatibility issues. I suggest that you first install the following in the specified order to ensure a smooth interfacing.

1. First install Java 8 JDK.

2. Install rJava library in R.

3. Install RNetLogo library in R.

4. NetLogo version 6.0.3.

RNetLogo relies on rJava, which itself relies on Java JDK 1.2 or higher. However, RNetLogo requires Java JDK 8 or higher. We recommend installing Java JDK 8. It should be noted that you can install multiple versions of NetLogo. You can specify the desired version to run in R.

Sensitivity Analysis

We conduct sensitivity analysis on two main assumptions. First, non-flippers or long-term homeowners discount their prices if the potential buyers do not accept their offers. The second is that flippers or speculators sell their houses with a markup. Our sensitivity analysis is conducted to study the effect of non-flippers' discounting assumption and the impact of the markup size by the speculators on the effect of both the search cost and number of flippers on the variance of the market average price. The results of the sensitivity analysis are shown in Figure 8, and Figure 9 . The analysis suggests that the results are robust to discounting and markup assumptions.

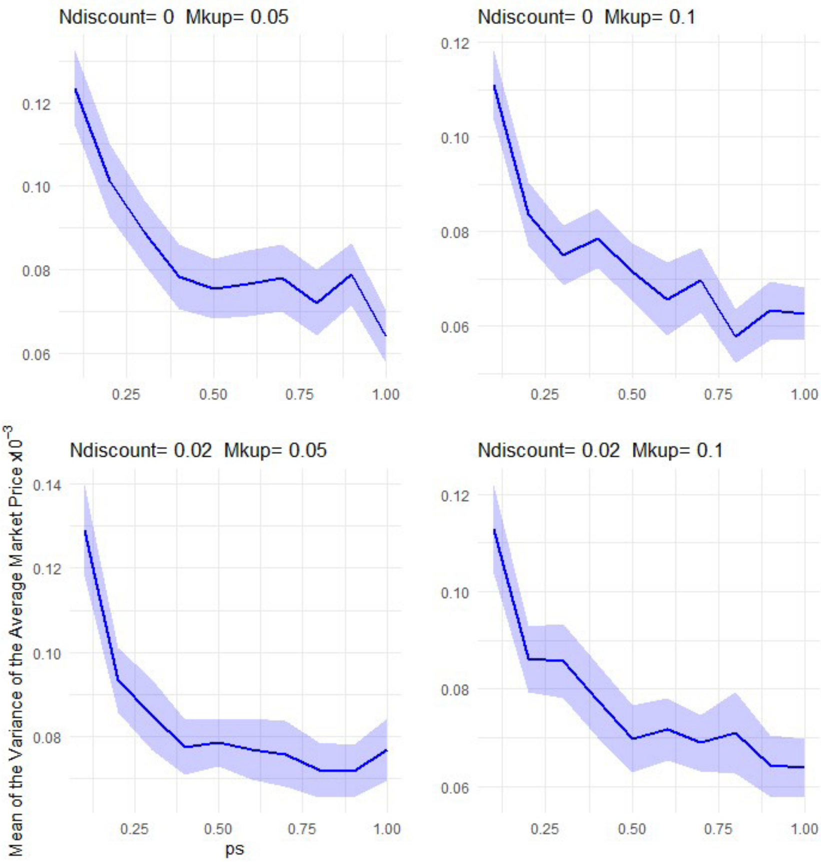

Figure 8: Sensitivity Analysis of the Effect of Search Cost on the Variance of Market Average Price

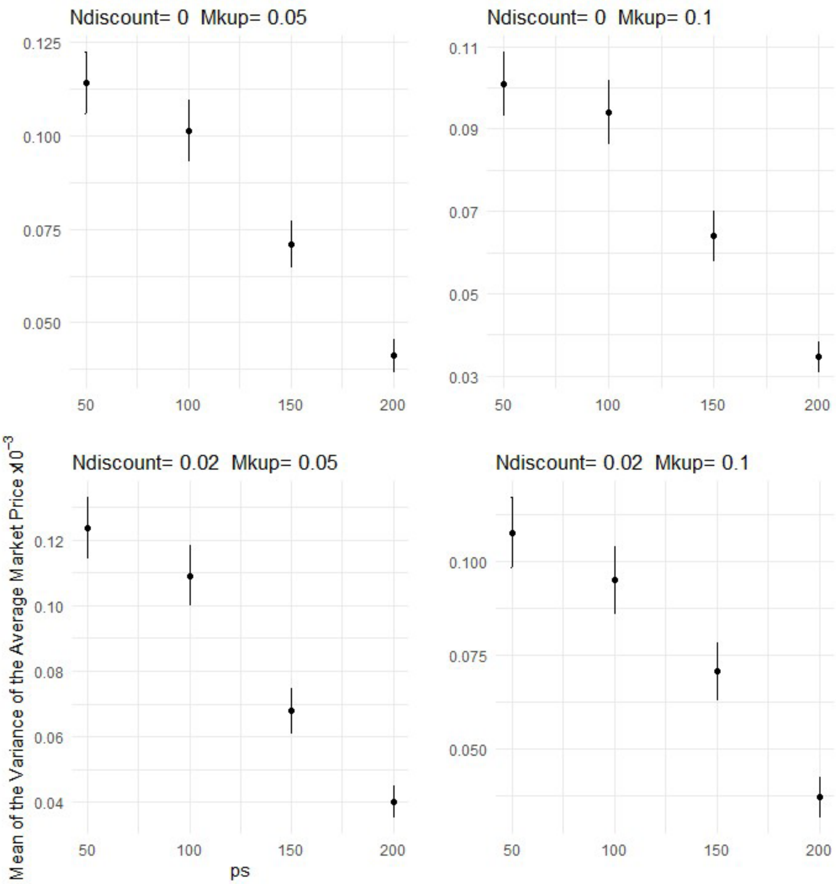

Figure 9: Sensitivity Analysis of Non-Flippers Discounting and Flippers Markup on the Effect of the Number of Flippers on the Variance of Market Average Price

Ebrahim Alebrahim is an Assistant Professor in the Department of Economics at Kuwait University. He earned a Ph.D. in Economics from North Carolina State University in 2020. His research interests include industrial organization, network economics, and behavioral economics. (ebrahim.alebrahim@ku.edu.kw)

Acknowledgment and Disclosures

The author extends his gratitude to Abdullatif Al-Rashdan for his valuable feedback on an earlier draft of this work, as well as to the anonymous reviewers for their constructive and insightful review.

حوليات الآداب والعلوم الاجتماعية
ANNALS OF THE ARTS AND SOCIAL SCIENCES

- مجلة فصلية محكمة.
- تصدر عن مجلس النشر العلمي بجامعة الكويت.
- صدر العدد الأول سنة ١٩٨٠م.
- تنشر الموضوعات التي تدخل في مجالات اهتمام الأقسام العلمية لكليتي الآداب والعلوم الاجتماعية.
- تنشر الأبحاث والدراسات باللغتين العربية والإنجليزية شريطة أن لا يقل حجم البحث عن ٥٠ صفحة وأن لا يزيد عن ٢٠٠ صفحة مطبوعة من ثلاث نسخ.
- لا يقتصر النشر في الحوليات على أعضاء هيئة التدريس لكليتي الآداب والعلوم الاجتماعية فحسب، بل يشمل ما يعادل هذه التخصصات في الجامعات والمعاهد الأخرى داخل الكويت وخارجها.
- تمنح المجلة الباحث خمسين نسخة من بحثه المنشور كإهداء.

KUWAIT UNIVERSITY • EXCELLENCE & INNOVATION • جامعة الكويت • 1966

رئيس هيئة التحرير

أ. د. تغريد القدسي

ثمن الرسالة للأفراد

(٥٠٠ فلس)

نوع الاشتراك	الكويت	الدول العربية	الدول الأجنبية
الأفراد	٤ دنانير	٦ دنانير	٢٢ دولاراً
المؤسسات	٢٢ ديناراً	٢٢ ديناراً	٩٠ دولاراً

جميع المراسلات توجه إلى رئيس تحرير حوليات الآداب والعلوم الاجتماعية

ص.ب 17370 الخالدية 72454 الكويت - هاتف 24830256 (965) فاكس 24830256 (965)

ISSN 1560 - 5248 Key title: Hawliyyat Kulliyyat Al-Adab

www.apc. kuniv. edu.kw/aass E-mail: aass@ku.edu.kw