AMERICAN UNIVERSITY OF BEIRUT

AGENT-BASED MODELLING OF FINANCIALIZED HOUSING MARKETS: THE EFFECT OF VACANCY TAX IN BEIRUT AS A CASE STUDY

by
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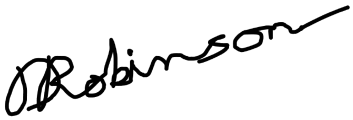

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ABSTRACT

Majd Majed Al-Shihabi for Master of Urban Planning and Policy
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Title: Agent-Based Modelling of Financialized Housing Markets: The Case of Vacancy Tax in Beirut

Financialization of housing is a well-studied phenomenon, which has many effects, chief among them is decreased affordability of housing, and high vacancy rates in urban centres. Many policy proposals have been put forward to mitigate those effects, among which is the adoption of a vacancy tax, which aims to increase the cost of holding vacant housing units and encourages owners to release the housing units to the sale or rental markets. Decision makers often look to make use of decision support systems, or computer models, to test the complex and emergent effects of their policy proposals in a "virtual world", before implementing them in the real world.

Among the many possible modelling paradigms, agent-based modelling (ABM) fits the intellectual tradition of urban planning, insofar it acknowledges the complex interactions between agents and allows for the emergence of bottom-up structures, as well as its adaptability to participatory planning processes. I use ABMs to develop a model that describes the effect of a vacancy tax on a financialized housing market, integrating patterns on multiple scales, including pricing spatial distribution, vacancy rates, and neighbourhood definition.

I apply the resulting model to the housing market in Beirut, using empirical data to calibrate it. I then run it for four scenarios, to examine the effect of a vacancy tax, the investment environment, changes in demand, and the search cost for households searching for housing. The results show vacancy rates decreased as vacancy taxes increased, demand increased, and with increased search time, but increased with higher interest rate offered from alternative investments. The most significant effect was from increased demand. Moreover, the effects were spatially heterogenous, with some neighbourhoods being more affected than others, depending on their class profile and proximity to important centres across the city.

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ABBREVIATIONS

ABM: Agent-Based Modelling

OPP: Object-Oriented Programming

PCH: Public Corporation for Housing

POM: Pattern-Oriented Modelling

DSS: Decision Support Systems

SDSS: Spatial Decision Support Systems

ODD + D: Overview, Design concepts, Details + Decision making

AUB: American University of Beirut

USJ: University Saint Joseph

LAU: Lebanese American University

BSRI: Buy, Sell, Rent, Invest

DEDICATION

To teta Im Majed, through her, I learnt the value of land.

CHAPTER 1

INTRODUCTION

Across the world, a housing affordability crisis is unfolding, with economic, ecological, and political implications (Wetzstein, 2017). Lebanon is no different. Lebanon's housing crisis has seen real estate prices skyrocket since 2005 (Ashkar, 2015), driving old tenants out of their homes, and resulting in the destruction of the built urban heritage of the city, making the city less livable for those who call it home.

The underlying current that is driving this change is financialization. In this section, I explore the implications of financialization on the housing sector and examine the complex dynamics using a systems lens.

1.1 Financialization of housing and the vacancy problem

1.1.1. The financialization of housing

Two of the defining characteristics of the capitalist mode of production are commodity production and capital accumulation. As those expand, they transform the underlying social processes. The pressure for survival within this environment encourages competition and the search for new profitable opportunities. Consequently, aspects of social life are turned into the commodities to be produced, accumulated, and consumed through markets (Forrest & Williams, 1984). For example, advertising companies such as Facebook and Google have commodified social relationships in order to sell them as hyper optimized and targeted advertising infrastructure (Doyle, 2015). Similarly, housing became a tradable commodity, driving a cycle of gentrification. Accompanying this shift, land turned into a "pure financial asset", where

its exchange value is prioritized over its use value (Harvey, 1989). Beyond the commodification of housing and as states became facilitators of financial instruments, housing became a conduit for capital accumulation (Forrest & Williams, 1984). This is a pattern that has taken place across the world, both in advanced capitalist economies as well as those on the peripheries (Aalbers et al., 2020).

While housing provision, whether by ownership or rental, has always had financial aspects, those aspects were heavily regulated by the state, or managed by financial institutions that were separate from other market institutions, particularly commercial banks. This protected the housing market from the volatility of the financial markets. Globally, states have slowly retreated from their role in housing provision and allowed financial institutions to play a more prominent role (Aalbers, 2017). This pattern of financialization is manifested spatially in many ways, including rapid gentrification, the destruction of built heritage, the displacement and evictions of tenants, urban sprawl, and environmental destruction. Those rapid transformations deprive city dwellers from their right to influence their urban environments and shape their city. In short, they are losing their right to the city (Aalbers & Gibb, 2014).

One of the many effects of the financialization of housing is the high vacancy rates in urban centres. The high visibility of such vacancies has rendered them into "sites of political antagonism". On a policy level, many interventions have been introduced that question the ability of property owners to leave their properties vacant (O'Callaghan et al., 2018). Urban planners and policy makers have a large set of possible policy tools and interventions to address the vacancy rates in their cities. These interventions can take different forms, operate at different scales, and be mediated

through different actors. Among such challenges is the imposition of a vacancy tax on vacant properties.

1.1.2. Vacancy tax as a policy tool

The toolkit available for urban planners and policy makers includes many possible solutions. Those include supply side incentives, demand side support, market regulation, land use interventions, and taxation tools (Fawaz et al., 2017). Among the many tax tools available, there is the option of implementing a vacancy tax that can be either set as a flat rate, or as a percent of the value of the property. It can also be set as a fixed percentage or as a progressive tax, based on tax brackets. Vacancy tax is usually leveed on housing units that are vacant for more than 6 months per year.

The implementation of a vacancy tax policy differs based on jurisdiction. In the United States for example, despite the lack of data on vacancies (Mosley, 2020), Oakland, California taxes vacant parcels at $6000/year, reducible to $3000/year for hardship cases (Tadayon, 2019). San Francisco is considering implementing a similar tax but for vacant store fronts (Pender, 2019). In Spain, the autonomous region of Catalonia already has a high vacancy tax and is planning on expropriating flats that remain unused for more than 2 years (O′Sullivan, 2020). The Toronto City Council has recommended the implementation of a vacancy tax, citing the precedent set by the City of Vancouver (City of Toronto, 2020).

The aim of the vacancy tax is to increase the cost of keeping a housing unit vacant, thus incentivizing landlords to lower their asking price for the housing units that they own, and thereby decreasing the rate of growth of the market. It can also force landlords that depend on tourist-oriented short-term rentals (such as AirBnB units) to

place their units on the long-term rental market, thus increasing the supply of available housing units.

1.1.3. Why study vacancy tax?

Vacancy rate is an important indicator of the shape of the housing market. Housing economists study an indicator called “natural vacancy rate”, which is defined as the vacancy rate at the equilibrium state of the housing market. It is unique to each metropolitan area. Deviation of the actual rate from the natural rate imply a disequilibrium in the market. Such deviation could be driven by a number of factors, including the supply of housing units, the maladjustments in the asking prices, or time spent by tenants seeking housing (Belsky, 1992).

Given the above reasons, it is clear that introducing interventions that aim to modify the vacancy rate is an important policy lever that policy makers can utilize to directly affect the housing market. In Lebanon, not only do vacant housing units not incur any vacancy tax, but they are also exempt from property taxes. In Beirut, research by the Beirut Urban Lab found that the vacancy rate in the city was around 23% in the housing units constructed in the 1996-2018 period. Fawaz and Zaatari (2020) enumerated the negative effects of this schema; these included incentivizing property speculation that deprive municipalities and ministries from much needed revenue streams and that encourage tax evasion.

The introduction of a vacancy tax in Beirut appears to be a promising policy tool towards helping regulate the rental market and reduce the vacancy rate. Yet, policy makers may need to be convinced by assessing its impact and evaluating its various implementation details. In order to systematically evaluate those alternatives, they could benefit from a decision support system.

1.2. Decision making in urban planning and policy

1.2.1. (Spatial) decision support systems

Traditionally, urban planners used their intuition to plan cities and develop policy interventions. They then started using computer models to validate their claims, especially in traffic analysis. However, there was a backlash against this modernist scientific approach (Hall 1988). Intuition is developed as a result of cumulative experience. In urban planning, such experience is difficult to achieve because of the long feedback times between policy design, implementation, and evaluation, especially in a context of evolving political, macro-economic, social, environmental, and electoral factors. In order to understand the dynamics of the interaction of those factors, policy experts can use decision support systems (DSS) to structure complex problems under theoretical frameworks (Sprague, 1980). When applied to spatially explicit problems, those systems are called Spatial Decision Support Systems (SDSS) (Armstrong et al., 1986).

With the support of a DSS, a policy maker can develop her intuition by moving between layers of abstraction, where she observes a system, identifies variables within it, adjusts those variables, and observes the results of those adjustments (Victor, 2011). In the process of understanding a problem domain, we often have to assess patterns at multiple scales. Victor (2011) states that one often has to "*step up a level of abstraction to see a high-level pattern, and then step down to discover the explanation for that pattern".* He concluded that this "*dance"* between these scales is where the deepest insights are born.

Urban policy DSS vary in their modelling paradigms, scope of methodologies, techniques, and contexts. Each DSS comes with its own methodological approach, as

well as its axioms and assumptions. Those techniques include cellular automata, Markov Chain models, spatial logistic regression, rule-based models, evolution trees, and multi-agent models. Each of those techniques is optimized for a different purpose, such as speed, resolution, inclusion of social concepts, and robustness and reliability (Jokar Arsanjani et al., 2013b).

1.2.2. Modelling and policy making

Over time and through experience, policy makers learn about the systems they are managing. Their learning takes the form of increasingly refined and nuanced mental models of the systems. For increasingly complex systems, such as the economy, policy makers require conceptual models in order to design their policies effectively. A classical understanding of the economy and markets seeks to formulate analytically tractable, simplified, and solvable equations that describe static equilibrium states (Arthur, 1999). A more comprehensive understanding of the economy describes it as a complex system, exhibiting all of the properties of complex systems, such as dynamic non-linearity, spontaneous ordering, path dependency, emergent properties, feedback loop dynamics, adaptation, and dynamic equilibrium states (Arthur et al., 2014). This process-oriented understanding of the economy is considered a paradigm shift in the conceptualization of the economy and markets, which has required the development and adoption of new tools for policy makers that allow them to learn and gain an intuition of the underlying dynamics of the system, and later identify leverage points for action.

A conceptual understanding of the economic system can thus be articulated as a model: this can take different forms, such as theoretical models, toy models, and idealized models, among others. A model then can be used to communicate the

underlying concepts, probe them with what-if scenarios, and then ultimately deepen learning about the systems that they describe (Frigg & Hartmann, 2018).

Morgan (1999) describes historical examples of the use of models in policy making. She describes a mechanical and a hydraulic flow model that described monetary policy in 19th century United States, constructed by Irving Fisher. She describes how the process of constructing the model, including the design decisions taken by Fisher, influenced the understanding of the underlying dynamics of the system he was seeking to describe. While models are not exact replicas of the empirical world, they do demonstrate a range of empirical phenomena that aid in understanding the complex systems they are describing.

Learning through models fits well within theories of learning. An often-described model of how learning works is a simplified three-stage loop, which starts with a policy maker learning something from their environment, the policy maker then uses the learning to make a decision, which in turn creates an effect on the environment. The policy maker then perceives the changed environment and reacts accordingly. This model, which is inspired by control theory, is not sufficient to explain learning by humans. For example, humans are capable of future prediction, which affects the decision making process. A later theory developed by Sterman (1994) argues that learning is best described by a triple loop model, as shown in Figure 1. In his paper, he describes the need for three necessary conditions that must be met for effective learning about complex dynamic systems to happen. These include:

(1) *The development of tools capable of eliciting participant knowledge, articulating and reframing their perceptions, and generating maps of any feedback structure based on their perceptions;*

(2) *The existence of simulation tools capable of assessing the dynamics of those maps and testing the impacts of new policies; and*

(3) *The presence of clear methods that allow for improved scientific reasoning needed to overcome defensive routines.*

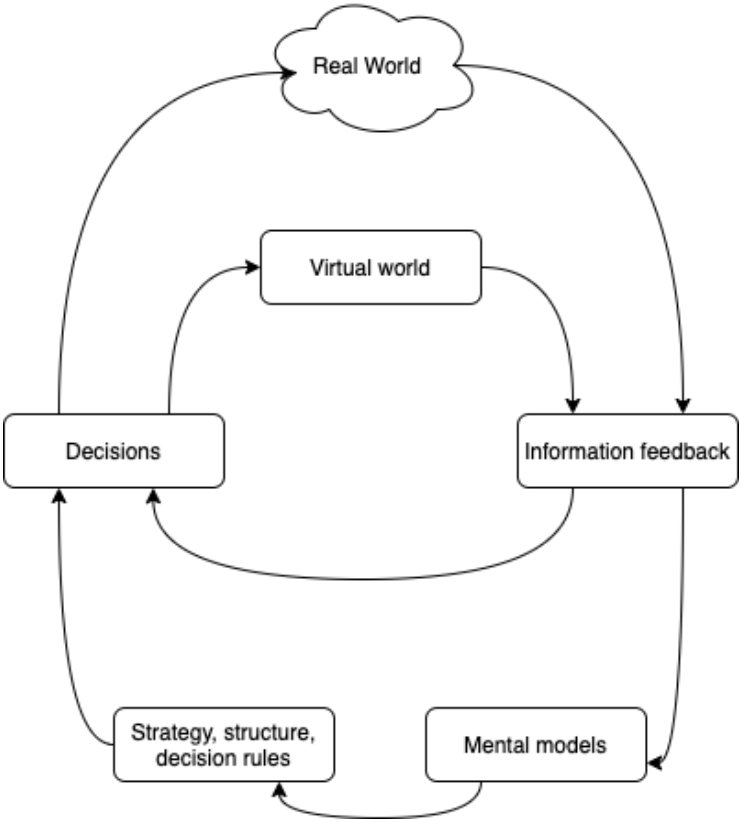

Figure 1: Idealized learning loops (Sterman, 1994)

The Sterman (1994) model of learning accommodates for the bounded rationality of policy makers, which reduces their ability to deduce cause and effect relations and to infer the dynamics of the complex system in which they are operating. This is particularly true in real estate markets, where a cycle can take as long as 25 years to complete, meanwhile market conditions are continuously changing. Since it is practically impossible to conduct controlled experiments in real estate markets, learning is significantly impeded, resulting in boom-and-bust cycles that often reward aggressive

and speculative real estate development behaviour and creating disincentives for conservative development. These further destabilize the market.

In this thesis, I aim to remove some of the impediments faced by policy makers, researchers, and city dwellers regarding their understanding of how housing markets work. I will create a virtual world, as specified in the Sterman model above, in which policy makers can refine their mental models of the market dynamics, and then test the implications of their policy proposals in this virtual world. The focus of this work will be limited to assessing the impacts of implementing a vacancy tax in a financialized housing market.

1.3. Research question, thesis argument, and significance

This thesis poses three questions, namely: "*How does a model of a financialized housing market looks like? What does the model tell us about the effect of introducing a vacancy tax on the housing market dynamics in Beirut? What other dynamics does the model reveal?*"

In this thesis, I propose a conceptual design for an agent-based model that uses multi-scaler and multi-lateral patterns observed in the literature about financialized housing markets. I follow this up with an implementation of the model by applying it to the Beirut market. Through this thesis, I argue that despite their limitations, agent-based models can be useful tools in the urban planner's toolkit. I aim to make the following contributions to the urban planning literature through this thesis:

1) <u>Create an agent-based model of a financialized housing market:</u>

   While agent-based modelling has been used to explore many urban phenomena, including land use/land cover changes, urban growth, and residential location

choice, very few models explored the roles of renters, buyers, and investors on the market.

2) Create a model that covers both the rental and the sale housing markets:

   The literature around housing markets tends to focus on the purchase market. Through this thesis, I conceptualize housing units as a stock that flows between the rental and sale markets, depending on the market conditions and incentives set by the state.

3) Explore the medium-term effects of the vacancy tax on the financialized housing of Beirut:

   I use empirical data on Beirut to apply and customize the conceptual model to the local context of Beirut.

4) Contribute an agent-based model that is rooted in the Global South to the global literature:

   While the phenomena that this model is describing has manifested itself around the globe, this particular model comes out of research done at the American University of Beirut, and owes its existence to the community of practice of urban planners in the region.

CHAPTER 2

METHODOLOGY
CONSTRUCTING AN AGENT-BASED MODEL OF RESPONSE OF REAL ESTATE INVESTORS AND DEVELOPERS TO VACANCY TAXES

2.1. Agent-based modelling as an urban planning tool

2.1.1. A systems approach to wicked problems

The theoretical approaches to urban planning as a profession have evolved over time, and in the process they produced different schools of thought that remain in dialogue with each other. One of the common elements among all approaches is that the goal of urban planning is to optimize the built environment for the well-being of city dwellers, while balancing the competing, often conflicting interests of the stakeholders involved, within the evolving constraints of the social, political, and environmental conditions (Hall, 1988). This understanding draws upon decades of qualitative and quantitative research in the fields of sociology, anthropology, economics, political science, psychology, and more.

In the case of housing and land markets, Zaatari (2019) reviewed the progression of their theoretical conceptions, starting with the universalist neoclassical economic model, where the individual is the ultimate rational decision maker (Molotch, 1993). This was followed by a shift to the institutional approach, where institutions define structures, thus creating strong and weak incentives that individuals act in response to over space and time (Jones & Ward, 2003, p. 15). Moreover, an actor-centred approach has also developed that is drawn from political economy, where individuals and institutions continuously interact and shape each other in a multilateral process,

producing spatially and historically specific outcomes (Garcia et al., 1994). In the sociology literature, this circular multilateral process of shaping and reshaping of actors is called structuration theory (Giddens, 1984). Chattoe-Brown (2013) contends that even though this seems to be an obvious truth, both qualitative and quantitative research methodologies have struggled in operationalizing that knowledge. One of the difficulties of operationalizing this result is the cumulative effect of the circular interactions between actors. This is known in systems theory as feedback: negative feedback regulates the system, positive feedback pushes it to grow and amplifies small changes (Morrison, 2005). This is a well-known result from non-linear dynamic systems that has given birth to the field of complex adaptive systems (Fieguth, 2017).

Going back to the case of housing markets, most macroeconomic studies of the housing market create models based on the behaviour of aggregated fictional "representative" individuals. They often create separate models for different represented groups. However, it is known that the *interaction* between those representative individuals creates *feedback loops*, resulting in patterns of behaviour that cannot be inferred from inspecting the individual actors alone. This is known in the literature as "emergent behaviour" (Lengnick, 2013). Urban planners and geographers recognize the complex effects of emergent behaviour very well. We call problems that exhibit such behaviour "wicked problems" (Skaburskis, 2008). Planners, especially those from the Global South, have been at the frontiers of the calls to embrace the complexity of wicked problems and resist approaches that flatten and simplify them. A very limited list of these includes decentering Western epistemologies (Roy, 2009), learning from informality (Fawaz, 2009), planning *with* complexity (Innes & Booher, 2018),

questioning the legal conceptions of nature in property law (Blomley, 2008), and countering colonial practices in agrosystems (Tesdell et al., 2020).

This key intuition that urban planners have developed, in which heterogeneous actors with their own agency and diverse interests produce systems with complex and emergent attributes, corresponds to the Sterman model of learning described in section 1.2.2 above. Urban planners often are in need of a "virtual world" in which they can test their ideas and policies and examine their implications. Such virtual worlds are *models* of the real world, which are created for the purposes of assessing the different aspects of the systems we seek to study. Since it is impossible to create a model of the entire system being represented, modellers have to select a purpose for their models. Thus, models are judged as tools designed for specific purposes, and the quality of a model is assessed against its declared purpose (Edmonds et al., 2019). In this case, models are a form of "purposeful representation" (Starfield et al., 1994). The map, perhaps the most commonly used tool by urban planners, is an example of a model with purposeful representation. While the map is not strictly correct in every aspect of the territory it represents, it is still useful for the purpose for which it was made (Korzybski, 1931) (Harley, 1989) (Kitchin, 2010).

Which among the modelling paradigms mentioned in section 1.2.1 fit this conceptual model that allows for multilateral feedback processes that can produce bottom-up emergent properties? Agent-based modelling (ABM) is one suitable modelling paradigm in this case, since an ABM by definition consists of heterogeneous agents that interact with each other in space and time, according to explicitly stated rules.

2.1.2. ABMs and urban planning

A major limitation of traditional modelling paradigms is that they simulate socio-economic variables, without attention to individual preferences and behaviours. ABMs provide a viable alternative to those paradigms, because they account for both macro-level variables as well as individual agent-level dynamic behaviours. Thus, they are adaptive and allow the users to gain a powerful intuition of the dynamics of a complex system. As such, ABMs can be used by policy makers to test out scenarios, allowing them to do what humans do best, which is to extract patterns, formulate hypotheses, and test them (Moss 2002).

ABMs can extend the tool kit of the urban planner by assisting in the process of exploring and generating possible futures (Epstein, 1999). Urban planners have fit ABMs to many of their existing practices; yet their adoption overall has been slow. ABMs have been used to understand urban dynamics since the 1990s (A. Heppenstall et al., 2020). Even earlier, Schelling used ABMs to understand how the preferences of individual households for similar neighbours can produce a pattern of spatial segregation in a city. Filatova and Parker (2009) simulated the development of a monocentric city using ABMs based on bid-rent theory, which they later expanded to coastal cities (Filatova et al., 2011). Meanwhile, Innocenti et al (2020) developed a design pattern for producing ABMs of land cover/land change models and applied it to housing in touristic areas, where intense competition for land increases housing prices. They modelled the roles of agricultural landowners, investors, households, and developers. Geanakoplos et al (2012) in their effort to better understand the role of finance in markets used ABMs to comprehend the driving cause of the 1997-2010 boom and bust cycle of the housing market in the United States. Jakar et al (2013a) used

ABMs to investigate the patterns of growth and development in Tehran over time. Zhuge and Shao (2018) developed a combined residential location choice and real estate price ABM and applied it to a medium sized Chinese city to identify the model variables that had the largest impact on the model output. It should be noted that the Zhuge and Shao (2018) paper is the only model where the rental market is modelled alongside the sale market.

In addition to responding to specific research questions, ABMs fit into the participatory planning paradigm quite well through participatory modelling. Participatory modelling takes many forms, but most importantly, it mandates that multiple stakeholder participate in the construction and design of the model, rendering the model into a "boundary object", whose artifacts (tables, maps, diagrams, etc.) form the basis for discussion, without requiring complete consensus on every part of the model (van Bruggen et al., 2019). Participatory modelling can also help planners in identifying the right questions to ask (Prell et al., 2007). Urban planning problems are also problems of democratic governance. Fawaz (2017) highlights the lack of democratic processes for setting and implementing urban planning agendas. As a boundary object, ABMs can provide a space for dialogue and facilitate learning by the wider swaths of city dwellers, allowing them facilitated access to tools used by experts.

2.2. Modelling approach and conceptual design principles

The initial research question that this thesis sets out to explore is the following: *What is the effect of introducing a vacancy tax on the housing market dynamics in Beirut?* This is a broad question that includes too many degrees of freedom, since the factors that possibly affect vacancy rates are numerous. In order to limit the number of

variables, I follow pattern-oriented modelling (POM) as an approach for building structurally realistic models. This approach is called the Medawar Zone (Grimm et al., 2005). The goal of POM is to include enough complexity to capture the structure of the system, while avoiding the problems of analysis that accompany overly complex models. As such, the central question of POM is *"What observed patterns seem to characterize the system and its dynamics, and what variables and processes must be in the model so that these patterns could, in principle, emerge?"* To answer this question, I relied on capturing three types of patterns. The first was based on the observations by Fawaz and Zaatari through the Beirut Built Environment Database project (Fawaz & Zaatari, 2020). Namely, they observed a spatial pattern of vacancies, with neighbourhoods containing higher numbers of luxury housing units having higher vacancy rates. In addition, they observed that corporate investors, making up 5% of developers in Beirut, produced 15% of the housing units. They suggested a multi-phased introduction of taxation schemes, where property taxes on vacant apartments are first restored, followed by an introduction of a progressive vacancy tax.

The second pattern that I accounted for was the large number of factors that affect housing unit selection by households. Arnott (1989) observed that "*Housing vacancies can be derived from three intrinsic characteristics of housing: (1) the multidimensional heterogeneity of the product; (2) the indivisibility (households cannot purchase fractions of different units and combine these fractions to obtain their ideal unit); and (3) the multidimensional heterogeneity of household tastes. These three characteristics of housing combine to render the housing market thin; even though there are many housing units, the dimensionality of the characteristics space for housing is so high that the units are sparse in this space*." This pattern gives investors almost monopoly power

to set housing prices, and indicates the importance of the attributes of a housing unit in determining its utility to a household. Finally, I tried to capture the pattern described by Mneimneh and Fawaz, where different developers have varying levels of access to financial institutions, risk and loss tolerances, and networks of clients (Mneimneh & Fawaz, 2019a).

As for processes, the most basic process is that housing units circulate in the housing market, changing ownership from investors, to households, and back to investors again. Another key process highlighted by Fawaz and Zaatari (2020) is the conceptions that investors have of their real estate holdings in Beirut. Particularly, they are viewed as investments that are stripped of their social function. They observed a reverse tax incentive, where real estate acts as a tax-free safe deposit box for capital accumulation, especially by Lebanese expats. This has a secondary effect of making land speculation a more attractive investment than investments in the productive sector. This process affects the decision making of investors, which must be represented in the model. The final process that was observed is that households that cannot find housing close to their budget point inside the city are thus forced to leave the city and seek housing elsewhere, while new households enter the housing market every year (Mneimneh & Fawaz, 2019a; Abou-Ibrahim, 2021).

Based on these patterns and processes, I defined the set of most important variables that need to be considered when constructing the model. I also defined the scales at which they operate. Table 1 shows a summary of the defined variables along with the scale of their operations. Figure 1 shows the patterns and their model representations in the model.

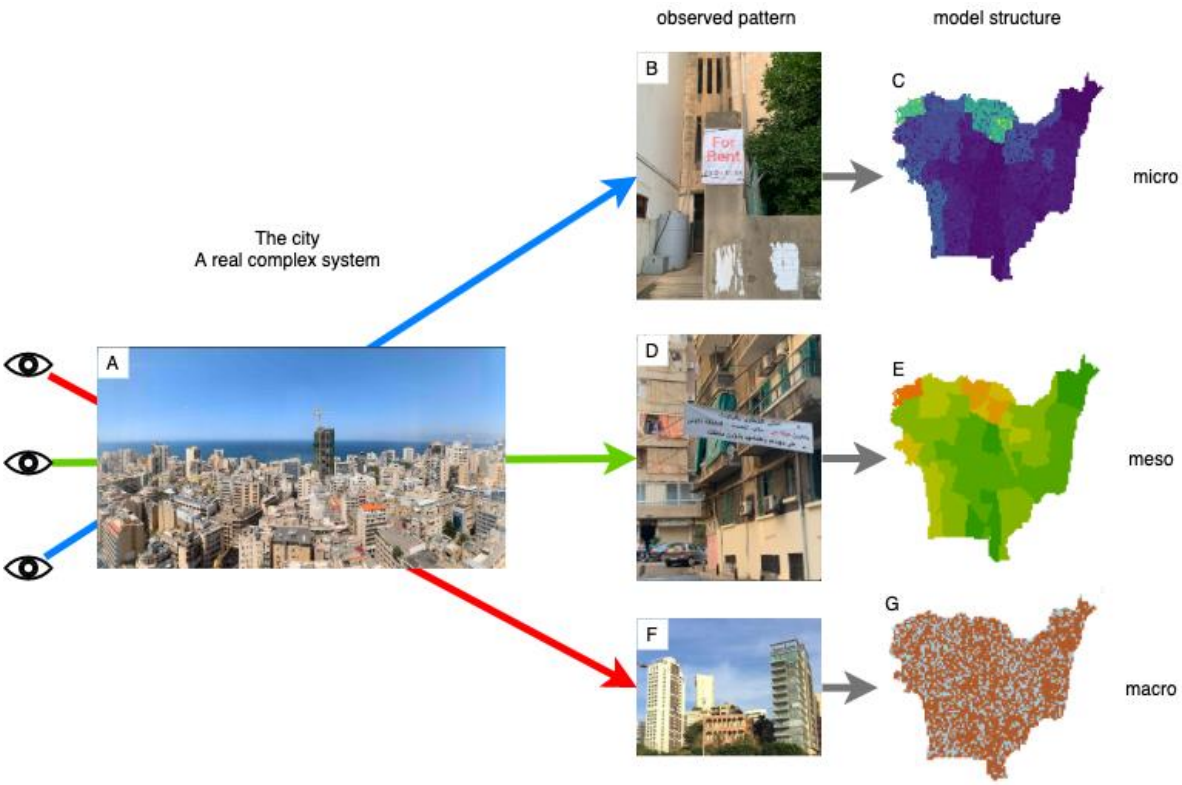

Figure 2 Patterns observed and their representations in the But/Sell/Rent/Invest (BSRI) model. A) the complex city as a system; B) micro level observation of housing units on sale/rent, with specific asking prices; C) Model representation of heterogeneous asking prices of each housing unit on the market. Each pixel is a housing unit; D) Neighbourhoods emerge in the city; E) neighbourhood asking prices are aggregated by neighbourhood, each colour patch is a neighbourhood, green is lower prices, red is higher; F) New buildings with many vacancies; G) Vacant housing units in blue, distributed across the city.

Table 1 Variables considered in creating the ABM model and their scales

Variable	Scale of operation
Vacancy tax, property tax	City scale
Investment environment	City scale
Number of households seeking housing (demand)	City scale
Wealth distribution	City scale
Rent laws (e.g. minimum legal length of contract, evictions)	Individual agent scale
Household budget	Individual agent scale
Household preferences	Individual agent scale
Housing unit characteristics (operating costs, amenities, proximity to selected locations)	Housing unit scale
Average sale and rental prices	Neighbourhood scale
Investor and developer behaviour (risk aversion, market knowledge)	Individual agent scale
Access to capital and financial institutions	Individual agent scale

The main principle for developing the model was to reflect the structure of the underlying system. However, I set additional constraints to the model development process in order to ensure that its utility is maximized among its intended users. First and foremost, I paid special attention to the future users of the model. As a model born from the urban planning tradition, I expect the model to be used by other urban planners in the future. The model must then include an easy-to-use graphical user interface for non-technologists to interact with it. For this reason, I used an ABM software

framework called Mesa (Masad & Kazil, 2015). Mesa is written in the Python programming language. It provides a familiar web-based interface, allowing users to view, interact with, and run experiments on the model from their own web browsers. This opens the door to a wide variety of uses for the model, including learning through exploration and experimentation, an essential part of the "virtual world" proposal put forward by Sterman (1994b). I also placed the code of model under the Anti-Capitalist Software License (version 1.4), explicitly permitting individuals, non-profits, educational institutions, and cooperatively structured organizations to exploit the model, while simultaneously prohibiting investors and financial institutions from using it without written permission from myself, the author.

2.3 Buy/Sell/Rent/Invest (BSRI) Model specification: definition and features

In the rest of this chapter, I propose a model that responds to the above questions. The model is called the Buy/Rent/Sell/Invest, or the BSRI[1] model.

The description of the model follows the "Overview, Design concepts, Details + Decision making" (ODD + D) protocol developed by Müller et al (2013) for describing ABMs. The goal of using this protocol is to communicate the model as clearly as possible and to facilitate the process of understanding, analyzing, and communicating it (Grimm et al., 2006). Using a standard protocol also has the effect of improving the reproducibility of the model, an essential component of the scientific process. A detailed table version of the protocol is attached in Appendix A. While I answer all the

[1] The name is a tribute to the Save Bisri Valley campaign, which is seeking to preserve the Bisri Valley from destruction resulting from a proposed dam project.

guiding questions posed by the protocol, I do not explicitly state each question within its structural element.

2.3.1. Overview

2.3.1.1 Purpose

Edmonds et al. (2019) outlined seven different purposes for creating models. This model aims to *describe* the effect of a vacancy tax on investor decision making in a financialized housing market. Particularly, it describes the effect of the vacancy tax and property taxes on the decisions of investors to place their units on the rental or sale market, or to hold them outside the market. The model does not aim to describe all aspects of the housing market, in particular, it does not describe informal housing patterns, the effect of sectarian dynamics, real estate development cycles, or state policy response to the evolution of the market. However, the model does provide a scaffolding for modellers to iterate on the model and adapt it to include those dynamics.

While the financialization of housing takes a similar shape across the world, I conceptualize this model with the case study of Beirut City in mind, relying on literature produced on the behaviour of developers and investors in the Beirut market. However, given the right data, the model is applicable to any other city in Lebanon, the region, or elsewhere where financialization is the main driver of housing markets.

In building the model, I pay particular effort to build a user interface that allows users to manipulate the model using a familiar web interface, showing them key visualizations that facilitate their understanding of the underlying dynamics of the complex system at hand. The users of the model do not need any coding experience to be able to run the model; however they do need domain knowledge to understand the available parameters and their effects.

2.3.1.2 Entities, state variables, and scales

There are four main entities represented in the model. These are: housing units, households, investors, and realtors.

Housing units have owners, who could be of two types, namely investors or households. They have an asking rent price and sale price, and once a housing unit is sold or rented, an actual price is negotiated. They can be placed on the rental or sale market, or neither. They have physical attributes such as condition, amenities, operating costs, and distance from important locations in the city (major university campuses and the Central Business District).

Households can be one of three categories: they can be "buyers", searching for a housing unit to purchase, and once they purchase a unit, they become "owners". Alternatively, they can be "renters". Each household has a fixed housing budget, and access to financing, including a specific interest rate and a down payment. They have a subjective preference for proximities to important locations within the city as specified by the location of each housing unit. They have a limited amount of time to view specific housing units before they bid on them for buying or renting.

Realtors are the information brokers of each neighbourhood. Each neighbourhood in the city corresponds to one realtor. The realtors keep a ledger of the transaction history, and from it, they calculate average rent and sale prices per square meter for housing units in their neighbourhoods on an annual basis.

Investors fall in two different categories, they can be "corporate" or "amateur". For the purpose of this model, I equate developers with investors. While not all investors are developers, in the paradigm of the financialization of real estate, all developers are investors in the real estate market.

Agents are driven principally by endogenous factors; however, there are two significant exogenous factors that affect their behaviour. First, there is a legal minimum duration of rental contract that creates a temporary protection for households from the possibility of losing the housing unit they have occupied for the past years. This is context dependant. In Lebanon, the new rental contract law of 2014 sets the legal minimum to 3 years (Bekdache, 2015). This slows down the turnover rate of housing units. Additionally, the investment environment set by the state drives the decision of investors to sell, rent, or hold the units off the market.

Space is explicitly defined in the model. The boundary of the system represented is the municipal boundary of Beirut city. When a household is unable to find housing within the city's boundaries, they leave the city and are assumed to resume their search outside the city, in the suburbs. Each housing unit is spatially positioned in the city's grid, and thus has attributes regarding the distance to selected locations in the city (university campuses, city centre). Each housing unit belongs to a neighbourhood, where a realtor acts as the information broker. The spatial resolution of the city is user-defined, but was set to be a 100 by 100 grid by default, roughly equivalent to 50 to 70 meters blocks. The temporal resolution of the model is one year per step. Within each time step, bids are evaluated in the order in which they are received, creating a more granular temporal resolution.

2.3.1.3 Process overview and scheduling

At the beginning of each time step, each realtor defines the average price per m^2 and the annual trend in house valuation for their respective neighbourhood. Next, a number of new households arrive to the city looking to rent or buy. Meanwhile, investors in the city have to decide if they place their units on the rent or sale market or

leave it vacant. Subsequently, the new households select and view a number of housing units nearest to their budget and that satisfy their preference list. They place their bids for each housing unit in the order of their subjective utility. In addition to investors that own the vacant units, some households that own the housing units in which they live may choose to flip the housing unit into an investment and thus become investors themselves. After all bids are placed, investors attempt to select a successful bid for their properties. If a bid is successful, then a trade is registered in the realtor's ledger. Unrented or unsold housing units are returned to the pool to start the cycle again the next year. New households that are not successful in renting or buying in a given time-step, are also allowed to repeat the cycle for a number of time steps before they give up and decide to leave the city to the suburbs. Figure 3 shows a general overview of this process.

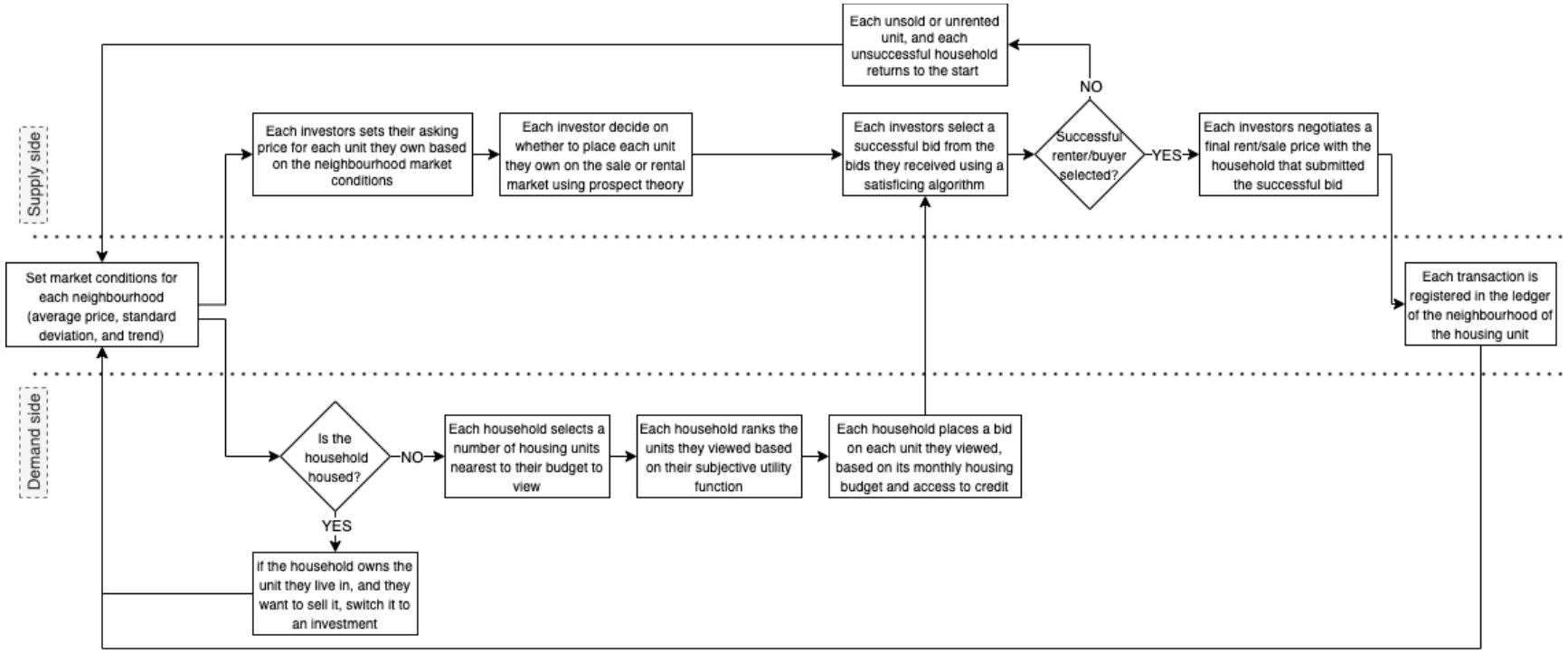

Figure 3 Process overview of the BSRI model

2.3.2. Design Concepts

2.3.2.1 Theoretical and Empirical Background

The paradigm at the core of the BSRI model is the financialization of the housing market, where housing units are traded principally based on their financial value. Thus, the main drivers of the model dynamics are financial. This implies an intentional exclusion of factors such as sectarian, familial, and other social affiliations. It also excludes macroeconomic trends such as gross domestic product and inflation rate, as well as geopolitical events, such as economic crises and abrupt loss of housing stock through mass destruction events the likes of the Beirut Port Explosion on 4 August 2020.

The model includes two decision making agents, namely investors and households. Both have bounded rationality in their decision-making process, which is manifested through limited perception. As such, households can only view a limited number of housing units in their search for a home. Investors are also bounded by the satisficing (satisfying and sufficing) stopping algorithm, when they have to select a bid among the bids received for their housing units.

Prospect theory (Kahneman & Tversky, 2013) was adopted in this model to describe the decision-making process of investors deciding on whether to place a housing unit that they own on the sale or rental market or to hold it as a financial asset for another time step. Prospect theory implies that investors treat choices that could lead to gains with a risk-averse attitude, while they treat choices that lead to losses with a risk-seeking approach. The choice of using prospect theory is important because it allows for the comparison of alternative investment choices, while accounting for psychological processes that affect human decision-making. This allows us to avoid the

assumption of perfect knowledge and rationality that is implicit in a profit maximization or even a utility maximization approach. Prospect theory has been empirically demonstrated to give more accurate results that resemble actual market behaviour more closely than purely economic approaches, such as expected value or expected utility (de Castro et al., 2016).

2.3.2.2 Study area and empirical data

The neighbourhoods' boundaries for the city of Beirut were defined largely based on the Electricité du Liban districts, with slight modifications to account for infrastructural division lines and to allow for a higher correspondence to the neighbourhood map developed by Ramco (Sakr, 2014). The data needed to initialize the rental and sale prices for the model as well the information required to determine the market trends were based on the Ramco data for the years 2015 through 2018. The Ramco data reports the price per meter squared for a first floor apartment across different neighbourhoods in Beirut. Further specifications of the study area are presented in Chapter 3 of this thesis.

2.3.2.2 Individual Decision Making

Households select the housing units to view based on their budget for housing. They evaluate each of the housing units according to their own subjective preferences, ranking them in order of their utility and placing bids based on that order. Through this process, they are maximizing the utility of their housing options, within their price range. They decide on the housing units to inspect solely based on their monthly housing budget. After viewing a number of housing units, they rank them based on their own subjective utility, which includes distance from important locations in the city as

well as apartment amenities. The weight between amenities and proximity to a city center is a subjective choice for each household.

Investors make three decisions. First, they decide on a sale and rent asking price for each of their housing units based on data from the realtor of their neighborhood. They then decide whether to place each unit for sale or rent, or to otherwise hold it off the market. Finally, if they opt to rent or sell, they choose a bid among the bids received for their units. Their goal is to maximize the subjective rate of return for their investment.

Asking price formulation is done based on the market trends for the neighbourhood in which the housing unit is located, as well as the subjective optimism factor of each investor; both of these are endogenous factors. The asking price is then used to calculate the subjective rate of return for waiting or renting. The rate of return is compared to the alternative investment subjective rate of return, and the unit is sold only if the alternative investment subjective rate of return is higher than that of renting or waiting.

Investors inspect the bids received for their housing units on the market in the order in which they are received. They accept a bid if it is higher than the asking price. Otherwise, they decrease their optimism factor and re-evaluate the subjective rate of return. If subsequently they still choose to sell, and if the bid price is higher than the lowest price they have defined, they accept the bid. Otherwise, they evaluate the next bid. The complete process demonstrating how a sale is processed in the model is shown in Figure 7. It should be noted that social and cultural norms play only a minor role in the decision-making process of the investors: amateur investors are influenced by anecdotal evidence, and thus have less accurate market knowledge. This is translated

into a probability weight parameter in the prospect theory calculation, thus introducing uncertainty in the investors' calculations.

2.3.2.3 Learning

While evaluating the bids received, investors are able to learn and update their probability of selling or renting their apartment at the asking price they formulated within the current time step. The probability decreases with every rejected bid that they inspect. Thus, they decrease their optimism factor and recalculate their prospect values after rejecting each offer. At the end of the time step, their optimism factor is restored to its initial value.

2.3.2.3 Individual sensing

Investors sense market conditions from their realtors. They detect two pieces of information on their environment. First, they sense the average price in the neighbourhood and use it to calculate their asking price. They then request from the realtors the probability of successfully renting a housing unit at the price that they have set. They also sense the precise interest rate offered by the central bank for investment deposits.

2.3.2.5 Individual prediction

Investors predict their expected sale and rent price based on market trends in their neighbourhoods. However, the price is not accurate due to its subjectivity, modulated through the investor's optimism factor and expectation weighing through prospect theory. Another source of failed prediction is an investor's stopping algorithm while evaluating bids, where they accept the first bid that meets their conditions, incurring a potential loss, because subsequent bids might be higher than the one selected.

2.3.2.6 Interaction

Households interact directly with the investors as they place bids for the housing units. Additionally, investors interact with each other indirectly, as their settled prices affect the final prices recorded in the realtor's ledger for the neighbourhood. This ultimately affects the asking price of other investors in the next time step. Those interactions depend on the budget of the households, which in turn determines the neighbourhoods that they can afford. Households also have a preference for locations in the city, which also affects their decision for locations to bid on. Political structures such as tenant unions, landlords associations, and investor groups are not represented in the model, thus there is no coordination among the agents.

2.3.2.7 Collectives

Households and investors do not explicitly belong to any collective. Sectarian affiliation, neighbourhood networks, and family networks are not represented in the model, while they can be very important factors in a city like Beirut.

2.3.2.8 Heterogeneity

In the model, investor agents were classified either as amateur or corporate. Research conducted by the Beirut Urban Lab was instructive for this classification. This corporate-amateur classification is a simplification of the corporate, professional, rising, and amateur developer classification that Mneimneh (2019) proposed for the Tariq el-Jdideh neighbourhood of Beirut. Zaatari (2019) also proposed a similar taxonomy, where she classifies developers in Aisha Bakkar and Tallet el-Khayyat neighbourhoods as corporate, neighbourhood, or amateur developers.

Mneimneh characterizes corporate investors broadly by their access to financial institutions, which permit them access to larger construction loans, as well as lower

interest rates. They tend to build larger projects, thus they own more housing units per investor. Their professionalized corporate structures mean that they have the resources and the obligation to conduct market research, and thus their knowledge of the market is more precise. They are also less loss-averse, because individual housing units are classified as assets in their accounting structures, with an expected appreciation in their value. This also has the effect of corporate investors having a higher subjective discount factor for their investments. Note that the subjective discount factor represents how much does the present value of an investment compare to its future value. This is effectively a measure of an investor's impatience. Since amateur developers would rather sell now rather than rent out their property and wait at least three years (the minimum legal length of a rental contract under the new rental law of 2014), they have a lower subjective discount factor as compared to corporate investors, who are under lower pressure to sell in order to fulfill debt obligations.

In contrast, amateur investors are numerous, but own fewer housing units, as they often build only one or two buildings before exiting the market. They are risk averse and prefer to sell as quickly as possible, giving them a lower subjective discount factor. They also prefer to pre-sell the housing units on the map, thus offloading the financial risks to their clients. This also results in reduced reliance on construction loans, but those loans come at higher interest rates. Their knowledge of the market is localized and comes through their direct social networks. Thus they have less precise knowledge of the market at large.

Table 2 shows the distinction between the two types of investors. In the table, relative terms such as "higher" and "lower" are used instead of specifying precise numbers for two reasons. First, in ABMs, the heterogeneity of agent characteristics is

more important than the precise numbers given (Crooks & Heppenstall, 2012). Second as this is a descriptive model, users are able to set the exact values for those parameters, allowing a user to experiment with those values to see their actual output. Household agents, housing unit agents, and realtor agents differ in all their attributes. The list of attributes and their default ranges for the household agents, the household units, and the realtors are detailed in Table 3, Table 4, and Table 5 respectively.

Table 2 Attributes of each category of investors

Attribute	**Brief description**	**Corporate investor value**	**Amateur investor value**
Housing units owned	The number of housing units owned by the investor	1-4	More than 4
Subjective discount factor	How much does an investor value their investment today, compared to a future date. Can be interpreted as a measure of impatience.	Higher	Lower
Loan size	The size of the loan compared to the price of the housing unit they own.	Larger	Smaller
Interest rate	Interest rate that the investor has access to	Lower	Higher
Loss aversion	Willingness to lose on an investment	Lower	Higher
Probability weighing	A measure of market knowledge, or conversely the susceptibility to anecdotal evidence. Possible values [0, 1]	Higher	Lower

Table 3 Default values for the household agents

Attribute	**Brief description**	**Value**
Breed	The type of agent	Buyer, renter, and owner
Budget	The monthly housing budget	Unlimited, in dollars
Down payment	Use for carrying capacity calculation	Minimum of 30%
Interest rate	Average interest rate a household has access to	5%
Location preferences	A numerical value for the each of the four locations	0-0.5
Amenity preference	Preference for amenities as opposed to distance	0-1
Units to view	Number of units to inspect while search and then eventually bidding on	1-20

Table 4 Default values for the housing unit agents

Attribute	Brief description	Value
Owner	The investor or household that owns the housing unit	Investor agent or household agent
Tenant	The household that currently resides in the housing unit	Household agent
Neighbourhood	The neighbourhood in which the housing unit is located	Realtor agent
Area	A number based on the neighbourhood that the housing unit is located in. Richer neighbourhoods have larger housing units.	[80-280] m^2
Price	Price at the time of purchase	Unlimited, in dollars
Price (rent)	Monthly rental price for that time step	Unlimited, in dollars
Asking price (sale)	The asking price for sale formulated by the owner	See equation (3
Asking price (rent)	Asking price for monthly rent formulated by the owner.	See equation (3
For rent	Whether or not the unit is on the rental market	True/False
For sale	Whether or not the unit is on the sale market	True/False
Condition	The maintenance condition of the housing unit	[0,1], where 0 is worst condition, 1 being the optimal
Operating costs	The monthly operating costs of the housing unit	Unlimited, in dollars
Proximity to AUB, USJ, LAU, and City Centre	The normalized value of the cartesian proximity from the location of the housing unit to each of the locations across the city.	[0, 1]
Amenities	Desirable attributes of the housing unit, such as building facilities, walkability of neighbourhood, etc…	[0,1]
Steps on market	The number of time steps that a unit has been on the market	> 0

Table 5 Default values for the realtor agents

Attribute	Brief description	Value
Neighbourhood	Name of neighbourhood	
Average unit area	Depends on the average prices of the neighbourhood	80, 140, 220 m^2
Housing units sold	A ledger of sale transaction in the neighbourhood history	List
Housing units rented	A ledger of rental transactions in the neighbourhood history	List
Average house prices sale	A history of average house sale prices for each time step, normalized by meter squared	List
Average house prices rent	A history of average house rental prices for each time step, normalized by meter squared	List
Price trend sale	A weighted average of house sale prices of the past three time steps, with the trend	
Price trend rent	A weighted average of house rental prices of the past three time steps, with the trend	

2.3.2.9 Stochasticity

Stochasticity is built into all layers of the model. The distribution of housing units between corporate investors, amateur investors, owner households, and renter households is assigned randomly using a uniform distribution across the city. As the model runs, the order in which agents make their decisions is shuffled between the households each time step.

Due to the lack of regional data for many of the attributes of the agents, they were set randomly, according to reasonable assumptions and statistical distributions. Most stochastic values followed a shifted-beta distribution when the range of values was fixed, or a gaussian distribution when it was not. There were a few notable exceptions: 1) household budgets were assumed to follow a Pareto distribution (Beckmann, 1969), with a distribution shape parameter set by the user; 2) the number of household arriving

in a city followed a Poisson distribution (Lin & Vandell, 2007), with a mean value set by the user; 3) when initializing the model, the number of steps that a household has been residing in a unit and the number of time steps a unit has been on the market were also assumed to follow a Poisson distribution.

2.3.2.10 Observation

In order to analyze the results of each model run, the model collects data on the following:

1) The number of rent and sale transactions at each time step,
2) The vacancy rate
3) The budget of households
4) The number of unhoused tenants
5) The number and budget of tenants that leave the city after not finding suitable housing
6) The tax revenue collected through each type of tax imposed

The emergence of the spatial pattern of the real estate investments over time will thus depend on the demand for housing, measured by the number of new household arriving into the city, the rate of return from the central bank bonds, the income distribution of those households, the tax schema imposed, as well as the time spent by households in the process of searching for housing. The model points to housing demand as one of the key drivers of the system dynamics.

2.3.3. Details

2.3.3.1 Implementation details

The model was implemented in the Python programming language, using the Mesa package for agent-based modelling. The code is available on the web at the following address https://gitlab.com/majdal/beirut-agent-based-modelling. The model is licensed under the Anti-Capitalist Software License. See Figure 4 for the sample graphical user interface of the model.

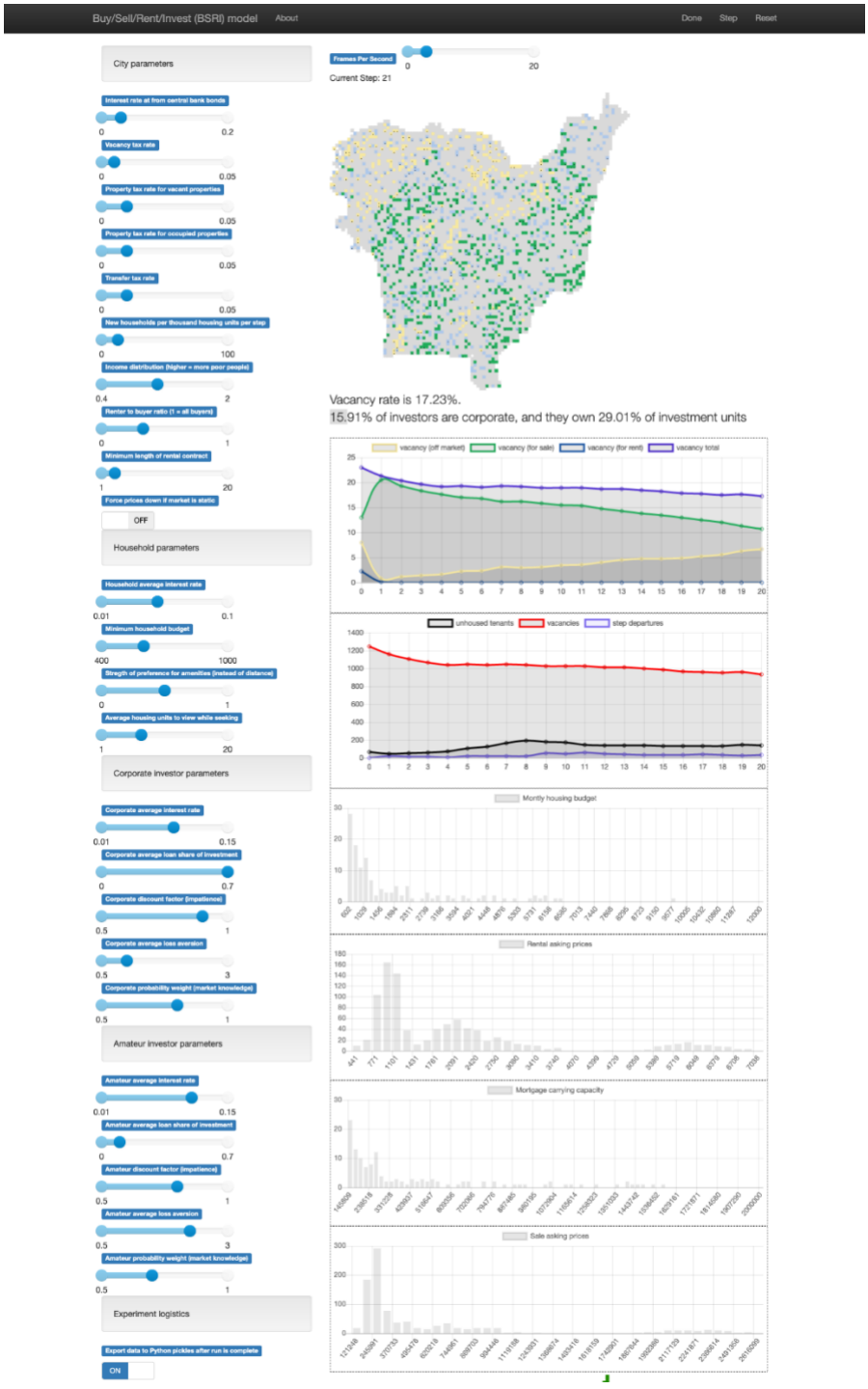

Figure 4 Sample user interface of the BSRI model

2.3.3.2 Initialization

During the initialization process, realtor agents are created for each neighbourhood. A price history for sale and rent in their respective neighborhoods are set. Housing units are then created with a uniform density over the city. Their distances to the four cores of the city (the American University of Beirut (AUB), University Saint Joseph (USJ), Lebanese American University (LAU), and the City Centre/Solidere area) are then calculated based on their location using Equation (1), where $\bar{P}$ is proximity to a location, D_{max} is the maximum distance of any housing unit to one of the core locations, and D is the distance of the housing unit to the closest core location. All distances are cartesian distances, and not dependant on the road network. The proximities are then normalized using Equation (2). Housing unit condition attributes were set to a constant value of 0.7 for all housing units, and homeownership operating costs were set to a constant 0.5% of the housing unit's price. Amenities were set stochastically by drawing a random number between 0 and 1 from a beta distribution with an $\alpha = 5$ and $\beta = 2$. A portion of the housing units were assigned randomly to household owners, and the rest to investors, corresponding to an owner-renter ratio set by the user, and set to 1:3 by default.

$$\bar{P} = D_{max} + 1 - D \quad (1)$$

$$P = \bar{P}/\overline{P_{max}} \quad (2)$$

Each investor is assigned a number of housing units, according to a Pareto distribution, with a shape parameter $\alpha = 2.5$. If an investor owns less than 4 housing units, they are given the category "amateur", otherwise, they are considered a corporate investor. Of the total housing units, 2% were assumed to be vacant and were placed on

the rental market, 13% were assumed vacant and placed in the sale market, and 8% were assumed vacant but held off-market by their investor owners, adding up to a 23% vacancy rate, as described by Fawaz and Zaatari (2020). The remaining units were either rented or currently owned by the households that live in them. The split between renters and owners was the defined to be the same as the ratio described above. The distribution of housing unit tenure and investment status is shown in Figure 5.

The realtors transaction ledger was populated for a number of timesteps back equal to the number of time steps in the average price history using the 2015, 2017, and 2018 data released by Ramco Real Estate Advisers. Finally, a number of new incoming households was added to the model, according to a Poisson distribution, with a mean set by the user. The default value was defined as 9.5 new households per thousand housing units in the city. Through this algorithm, each time the model is initialized, it will produce a different realization of the city with distinct spatial pattern of housing unit tenure and investment status.

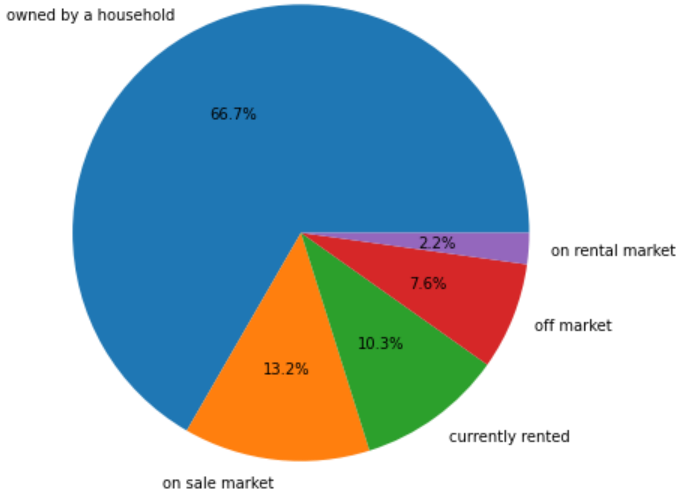

Figure 5: Housing unit tenure and investment status at initialization

2.3.3.3 Input Data

Neighbourhood boundaries were extracted from the Electricité Du Liban districts. Ramco Real Estate Adviser data were used for price trend history.

2.3.3.3 Submodules

When an investor wants to evaluate what to do with a housing unit they own, they set an asking price for rent, and an asking price for sale for the housing unit. Those are calculated using Equation (3), where $p_{average}$ is the neighbourhood average price for rent or for sale per square meter, a is the area of the housing unit in question in m^2, τ is the price trend for the neighbourhood in which the housing unit is located, and ψ is the optimism factor of the investor.

$$P_{asking} = p_{average} \cdot a \cdot \tau \cdot \psi \quad (3)$$

Investors decide on whether to place their housing unit on the sale or rent market, or to hold it off the market, by calculating the rate of return for waiting or renting using Equations (4) and (5) and the variables defined in Table 6. Investors then compare these rates of the return from an alternative investment, which in this case is the liquidation of the property and investing in government bonds. They do so by evaluating the prospect value of each of three prospects: 1) rent the housing unit while risking not finding a renter; 2) hold it off the market for one time step, or 3) liquidate the housing unit and invest in a central bank bond, while risking losing the investment due to a potential financial collapse. If the prospect value of renting is less than the prospect value of the bank bond, then the unit is placed on the sale market. If the rent prospect value is greater than the prospect value of the bond, then the unit is placed on the rental market. Otherwise, the unit is held off the market until the next time step. The

process is illustrated in Figure 7. Additionally, Figure 6 shows the rate of return for a range of potential rental prices set by a potential investor.

$$V = capital\ gain - interest\ due + rent - operating\ costs \quad (4)$$

$$x = \frac{V}{D} = \frac{\delta(1 + \dot{p} - (1 + r)m) + \rho - \kappa - t}{1 - m} \quad (5)$$

Table 6 Variables used for the calculation of net capital gains

Variable	Explanation	Possible values
V	Net capital gain over 1 year (in $)	$[-\infty, \infty]$
D	Down Payment (in $)	$[0, \infty]$
x	Rate of return (%)	$[-\infty, \infty]$
δ	Subjective discount factor (dimensionless)	$[0,2]$
$\dot{p}$	Rate of appreciation since purchase $\frac{p_T - p_0}{p_0}$ (dimensionless)	$[-\infty, \infty]$
r	Interest rate for investor (%)	$[0, 100\%]$
m	Mortgage share of price (%)	$[0, 100\%]$
ρ	Rent share of price, based on asking from equation (3 (%)	$[0, 100\%]$
κ	Operating costs share of price (%)	$[0, 100\%]$
t	Taxes share of price (%)	$[0, 100\%]$

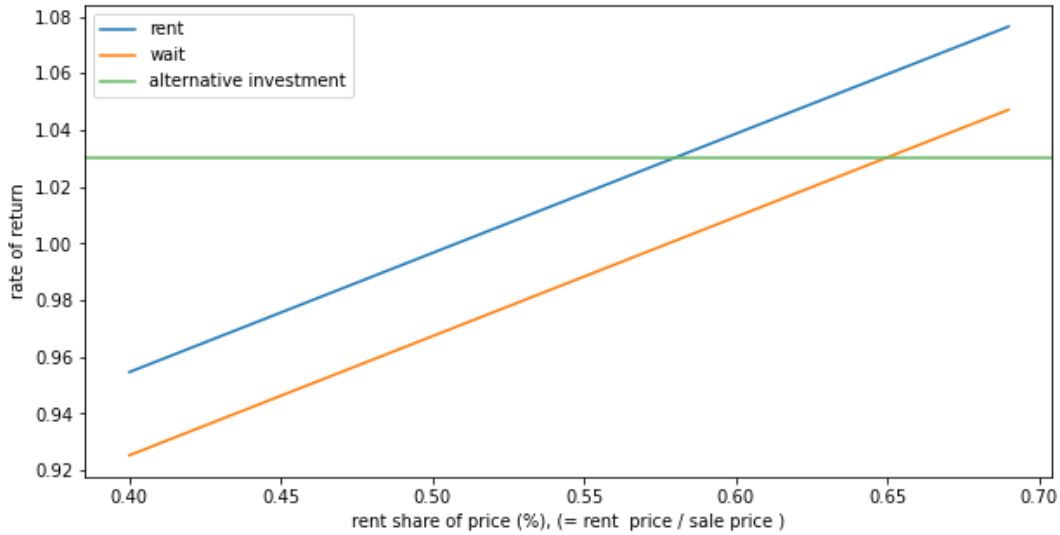

Figure 6 The variability in the rate of return for the rent and wait options as compared to an alternative investment as a function of different monthly rent prices (monthly rent in terms of % of housing unit price)

Once an investor decides on a rate of return, they evaluate the subjective value of the rate of return based on their individual market knowledge and risk assessment. This is done using the prospect theory calculation as shown in Equation (6.) The prospects considered are outlined in Table 7.

Table 7: Prospects that an investor evaluates when making a decision

Prospect	**Possible outcomes**
Rent	P: is the probability of finding a renter based on the asking price 1-P: Not find renter and pay vacancy taxes
Wait	100% probability of paying vacancy tax
Alternative investment	99% chance of getting alternative investment rate of return set by central bank 1% chance of losing 60% of the value of the investment

$$PTV = \sum_{i=1}^{n} w(p_i)v(x_i) \tag{6}$$

Where x is the rate of return as calculated using Equation (5), $v(x)$ is the subjective value of the rate of return calculated using Equation (7), and $w(p)$ is the weighted probability of an outcome i as calculated using Equation (9). The value n represents the possible outcomes for each of the three prospects defined in Table 7. For rent there are two outcomes (rent or pay vacancy tax); for wait one outcome (pay vacancy tax); and for alternative investment there are two outcomes as detailed in Table 7.

$$v(x) = \begin{cases} x^{\alpha}, & x \geq 0 \\ -\lambda(-x^{\beta}), & x < 0 \end{cases} \tag{7}$$

Equation (7) describes the weighted value of the rate of return, where λ is the loss aversion factor, and α, β are the gain and loss attitudes respectively. They signify a different attitude for large gains as compared to small gains, and large losses as

compared to small losses. Due to the lack of data, it was assumed that those two values are equal to 1. Moreover, the rate of return of each outcome was weighed by the probability of that outcome occurring $p(x)$. The probabilities were based on a Poisson distribution, as described in Equation (8).

$$p(k) = \frac{\varsigma^k e^{-\varsigma}}{k!} \tag{8}$$

Where ς is the arithmetic average of the length of time a housing unit stays on the market in a particular neighbourhood. To calculate ς, the realtor inspects the ledger for housing units sold or rented within +/- 5% of the asking price and calculates the mean number of steps they were on the market. If no units were sold within that price range, the average length of time for all housing units in the ledger is used instead. The investor calculates the probability of renting his/her apartment in the current time step by setting k to be 1 in order to signify the probability of finding a buyer or a tenant within the current time step. For each outcome, the probability of the outcome is then weighed to get $w(p)$ as described in Equation (9), where γ is the probability weighing function shape parameter.

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}} \tag{9}$$

While precise values for λ and γ are difficult to estimate (Nilsson et al., 2011), having heterogeneous values for different categories of investors is a more important factor for the structure of the model (Crooks & Heppenstall, 2012). The initial values defined in the BSRI model are shown in Table 8. All values, with the exception of the subjective discount factor and the probability weight (γ), were assumed to follow Gaussian distributions. Those two factors were assumed not to vary.

Table 8: Initial values for corporate and amateur investor attributes

	Mean		Standard deviation
Parameter	**Corporate investor**	**Amateur investor**	
Subjective discount factor	0.9	0.8	0
Loss aversion (λ)	1	2.25	0.065
Probability weight (γ)	0.8	0.7	0
Interest rate	9%	11%	0.1%
Loan share of housing unit price	70%	10%	1%
Optimism factor	1	1	1%

Ultimately, households decide to place a bid based on their housing budgets. They evaluate the utility (U) of the housing unit using a Cobb-Douglas function as shown in Equation (10), where z_i are the proximity and amenities attributes of the housing unit, and ξ_i are the household's preference for each attribute. The preferences are numbers that ranges between $[0,1]$ and that have to sum up to 1. Based on these utilities, each household ranks its bids in descending utility.

$$U = \prod_{i=1}^{m} z_i^{\xi_i} \tag{10}$$

The order in which households place their bids is shuffled each time step. The order in which investors evaluate their bids is also shuffled. However, each investor evaluates the bids they received in the order in which they were received. If a bid is above the asking price, then it is accepted. Otherwise, the investor's optimism factor is decreased by 1%, and the prospects values are recalculated. If the new choice remains for selling, then the next bid is considered. If it is higher than the lowest asking price,

then the bid is accepted. This is proxy to a sub-step time scale. It implies that the first bid that either satisfies or suffices the investor's minimum conditions will be chosen.

The circulation of housing units back on the market happens through two mechanisms: an investor could evict the tenant after the legal minimum contract length is over, freeing the housing unit to re-enter the decision-making process above. Alternatively, a household decides to turn their housing unit into an investment. In that case, ownership of the housing unit is moved from the household to an investor, and the investor continues with the decision-making process as described above.

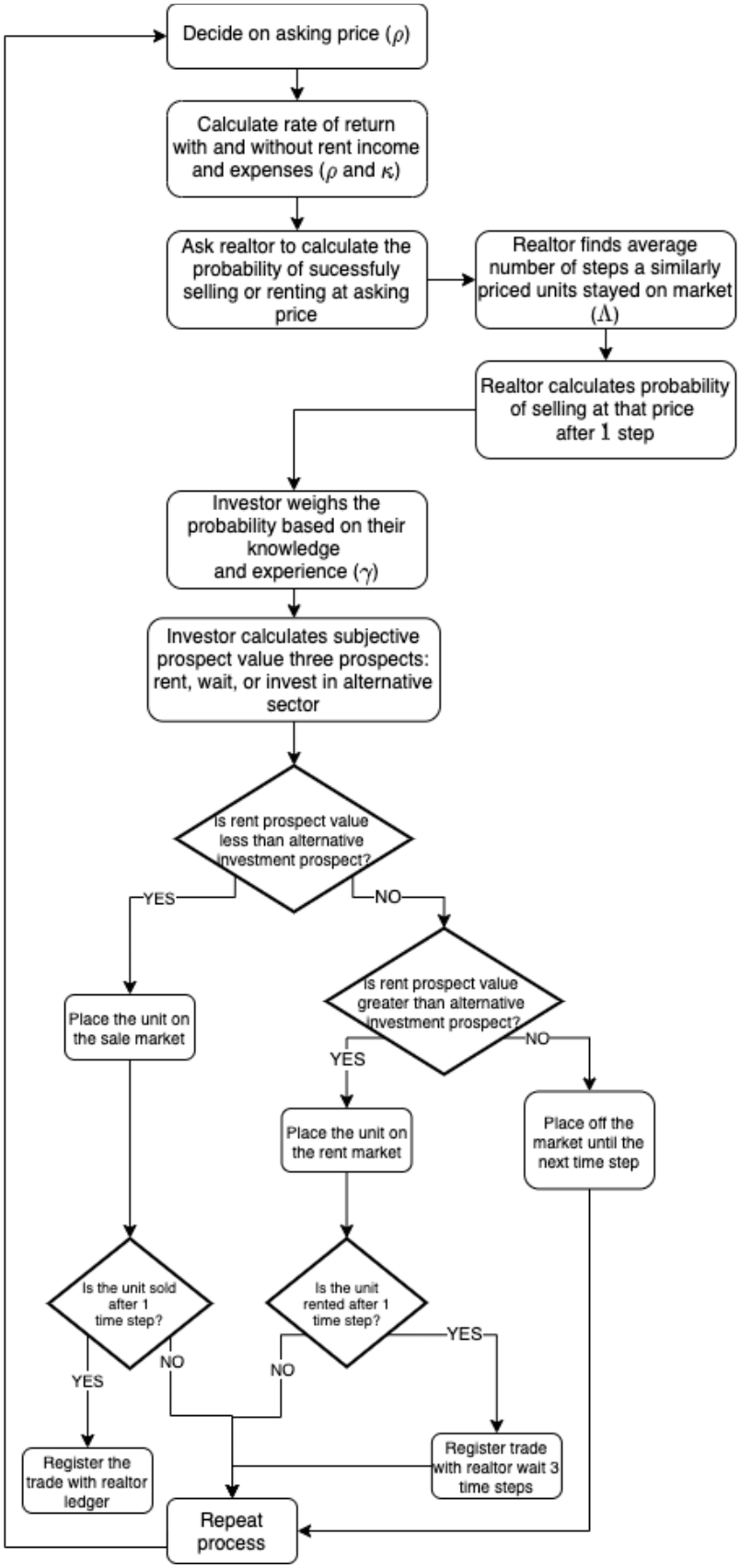

Figure 7 Decision making process by investor

CHAPTER 3

CASE STUDY
APPLYING BSRI MODEL TO MUNICIPAL BEIRUT

In this chapter, I apply the BSRI model developed in Chapter 2 to the specific case study of the city of Beirut. Beirut is the capital city of Lebanon, laying on the eastern Mediterranean coastline. Lebanon in the 1990s went through a time of transformation, after 15 years of civil war and the start of post-war reconstruction. This period saw the advent of the Public Corporation for Housing (CPH), the main government body that is tasked with housing provision in the country. The CPH adopted a market-driven approach of housing provision, relying mostly on housing loans as an intervention (Marot, 2018). This is an approach that reflects a global trend that was driven by the recommendations of the World Bank (Buckley & Kalarickal, 2006). While the Lebanese state has never been an active participant in the production of social housing, it nevertheless adopted the policies of the World Bank, leading to a the entrenchment of the role of financial institutions in shaping housing policy (Marot, 2018). The dominant form of housing provision has thus been characterised by decentralization and informality, particularly with regards to the urban planning processes (Krijnen & Fawaz, 2010).

3.1. Agent-based models of Beirut

While ABMs have been used globally to study a wide range of urban phenomena, only one attempt has been previously conducted in Beirut. Picascia et al. (2018) developed an ABM to study urban regeneration dynamics in Beirut in the face of

population influx, with an emphasis on accounting for the effects that the Syrian refugees had on the property market. Their model used rent-gap theory to explain the dynamics of investment in housing, resulting in a model of urban regeneration and decay.

3.2. Running the BSRI Model on Municipal Beirut

The BSRI model focuses on assessing the impacts of introducing a vacancy tax in the city with a focus on housing units built between 1996 and 2018. This decision was based on the fact that those housing units were built in the post-war period in Lebanon; a period that saw the advent of the PCH that is the main government institution tasked with urban housing production (Marot, 2018). Housing units produced during that period are more likely to fall into the financialization paradigm that the model is describing. Moreover, more data is available on that period, allowing for the proper initialization the model. Most of the data on the buildings from that period were provided by the Beirut Urban Lab (Fawaz & Zaatari, 2020).

According to Belsky (1992), each urban fabric has its unique natural vacancy rate that is affected by the demand for housing and the length of time a household spends searching for a suitable housing unit. Based on research conducted by the Beirut Urban Lab, the vacancy rate across the city for the buildings built between 1996-2018 was estimated at 23%, with 8% being sold but uninhabited and the remaining 15% being built but remaining unsold (Fawaz & Zaatari, 2020). This vacancy ratio was used to initialize the model. Moreover, the model was initialized with the assumption that the built but unsold units were distributed between apartments that are placed on the market

for sale (13%) and the remaining 2% were assumed to be on the rental market. The model also assumed that the supply of housing units was constant over time.

The initial prices of apartments per neighbourhood was taken from data published by Ramco Real Estate Advisers for 2015, 2017 and 2018. Linear interpolation was used to hindcast the 2016 data. The model also assumed that the only alternative investment for investors was the purchase of Lebanese government bonds. Additionally, the model assumes a constant 1% risk of a 60% loss in the value of their investment if an investor opted for these bonds. This assumption was made to reflect the potential of an imminent economic collapse. Furthermore, a Pareto distribution of wealth with a shape parameter of 1.11 was adopted for Beirut. This distribution produces a Gini coefficient of 0.819, corresponding to the Gini coefficient value for Lebanon in 2019 (Credit Suisse, 2019).

Several scenarios were defined and tested. Each of these scenarios was allowed to run over 20 time steps, with each time step representing 1 year. For each scenario and for each run, the initial state of the city was stochastically generated. As such, thirty future city states were initiated and run in an effort to capture model variability and assess the strength of statistical trends. Figure 8 shows a sample sale price distribution as well as the state of housing unit tenure at initialization. Note that each pixel in the figure corresponds to a certain housing block that contains a fixed number of housing units per pixel; the model disregards urban density and assumes that each pixel holds a single housing unit. The model contains 5,427 housing blocks in total. The model samples a maximum of one housing unit per block (sampling without replacement) to aid in the visualization of the city.

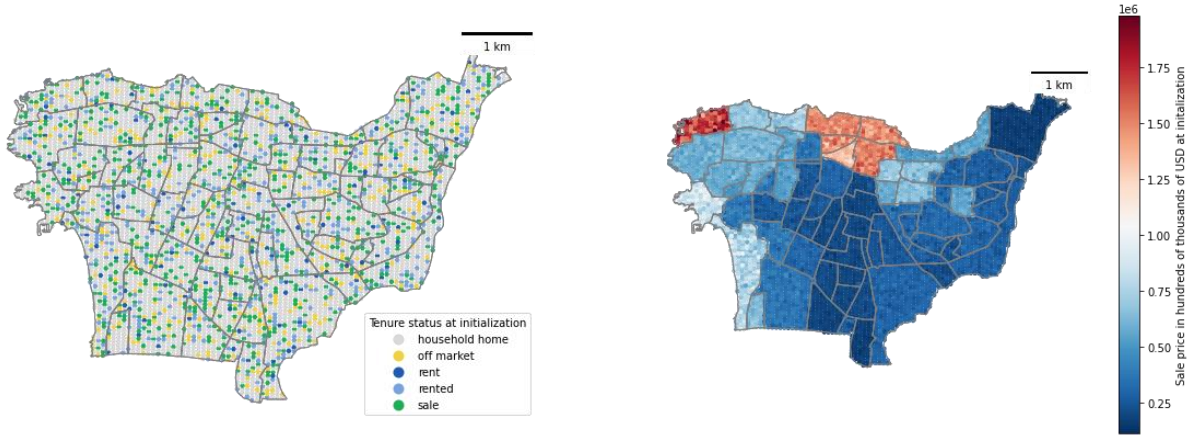

Figure 8 Random initialization of housing unit tenure distribution and sale prices by neighborhood across Beirut

3.2.1. Scenario definition

In order to understand the effects that introducing a vacancy tax has on the city, a set of scenarios were defined to test the effect of a gradual increase in the vacancy tax leveed on the vacant apartments in the model. Furthermore, the effectiveness of the vacancy tax when 1) alternative investment options were made available, 2) demand for housing changed, and 3) the urgency for purchase varied was also tested. In an effort to test the sensitivity of the vacancy rate to changes in these parameters, we decided to fix all other variables and to vary only one variable at a time. The defined scenarios are summarized in Table 9, while Table 10 lists the model parameters that were set as constants across the scenarios. Note that across all scenarios the initial vacancy rate was always set to 23%.

Table 9 Defined scenarios to run on the BSRI model

Scenario parameter	**Default value**	**Range over which it was varies**
Vacancy tax rate (sum of vacancy and property tax on vacant housing units)	2%	[0, 2%]
Mean number of new households arriving in a city per thousand housing units per year	9.5	[6, 17]
Central bank interest rate	10%	[1%, 13%]
Number of units a household views in their search	10	[5, 16]

Table 10 Fixed model parameter in the BSRI model across all scenarios

Parameter	**Value**
Income distribution shape parameter for the Pareto distribution (α)	1.11
Renter to buyer ratio	1:3
Minimum length of rental contract	3 time steps (years)
Household average interest rate	5%
Household minimum housing budget	$600
Household strength of preference for amenities	0.5
Corporate investor interest rate	9%
Corporate investor average loan share of investment	70%
Corporate investor discount factor	0.9
Corporate investor loss aversion factor [2]	1
Corporate investor probability weight [3]	0.8
Amateur investor interest rate	9%
Amateur investor average loan share of investment	70%
Amateur investor discount factor	0.9
Amateur investor loss aversion [4]	1
Amateur investor probability weight [5]	0.8

[2] For a discussion of this variable, see section 2.3.3.2
[3] Ibid.
[4] Ibid.
[5] Ibid.

3.2.2. Scenario 1: The effect of the vacancy tax

This scenario investigates the effect that the introduction of a vacancy tax will have on the Beirut housing market over 20 years. We assumed a cumulative vacancy tax value that includes both the property tax and the vacancy tax. Different vacancy taxes ranging between 0 and 2% were considered with an increment of 0.5%. For each of the selected vacancy tax, 35 future city states were initiated, and their status after 20 years was recorded. As can be seen in Figure 9, the vacancy rate after 20 years decreased as the vacancy tax increased. On average, the rate of the decrease was estimated to be around 0.4% for each 1 % increase in the vacancy tax. Note that even when the vacancy tax was set to 2%, the vacancy in the city did not drop below 19% with some simulations showing vacancies higher than the original 23%. Regardless of the vacancy tax rate leveed, most of the housing units that remained vacant were on the sale market rather than on the rental market as shown in Figure 10. Interestingly, very few apartments that were up for rent remained vacant, indicating that housing units that go on the rental market were immediately rented out if they were reasonably priced. Figure 11 shows the spatial distribution of mean sale and rental price increase, as well as vacancy rate by neighbourhood across the 35 future city realizations when the vacancy tax was set to 0% and 2%. Vacancy rates across the city varied between 6% and 33%. Reduced vacancy rates were most visible in the high-income neighbourhoods north of the city, where the vacancy tax pushed investors to put their units on the market and where there was a demand for such units given the proximity to the defined city centers. Additionally, low-income neighbourhoods had the lowest vacancy rates, as low-income households rushed to fill those housing units. It is important to note that even though the vacancy rates were assumed to be uniformly distributed at 23% across

the entire city at initialization, the model produced a differentiated pattern that was neighbourhood specific. As for the changes in the rental and sale prices, locations such as Ramlet Al Baida on the east coastline saw the largest drop. This could be attributed to the high price at initialization, while that area was the farthest from the four defined city centers locations and as such that affected the household utility calculations, resulting in a low utility. As a result, housing units there had lower ranking in the bidding process. Overall, the results point to a dynamic that funnels higher-income households to specific neighbourhoods that are closest to the locations to which proximity was calculated, and thus future iterations of the model should take other housing attributes into account when calculating utility. Additional attributes can be derived from hedonic price modelling.

The mean rental prices appreciated most in middle-income neighbourhoods such as the Badaro neighbourhood in the south-east of the city, likely due to its proximity to USJ campus and its starting low prices. Badaro is a neighbourhood that has witnessed a significant gentrification over the past years, and thus creating a rent-gap that drives this change, a pattern matched by the model. However, most of the city saw only a small increase in rental prices, and effectively no decrease in rental prices. At large, comparing the 0 % to the 2% tax scenarios, we observed that the spatial patterns were consistent and the changes in the sale prices were marginal.

Finally, in order to understand the structural dynamics of the model, it is important to step down to a single instance of the model to reduce the abstraction, as described by Victor (2011). Figure 12 compares two example cities after running the model for 20 years, one with a 0% vacancy tax and the other with a 2% tax. While Figure 11 shows an increase in rental prices, the high demand for rentals caused the

vacancy rates to remain lower than those observed under the 0% rate case. This can be attributed to a large pool of demand, as the number of households seeking housing is always greater than the number of housing units on the market, a dynamic described by Arnott (1989). Additionally, sale prices increased notably in the higher-income neighbourhoods in the city, in turn encouraging speculative investment and driving up vacancy rates, in a feedback cycle, which can be seen in Figure 12, where off-market units tend to be located in a few neighbourhoods.

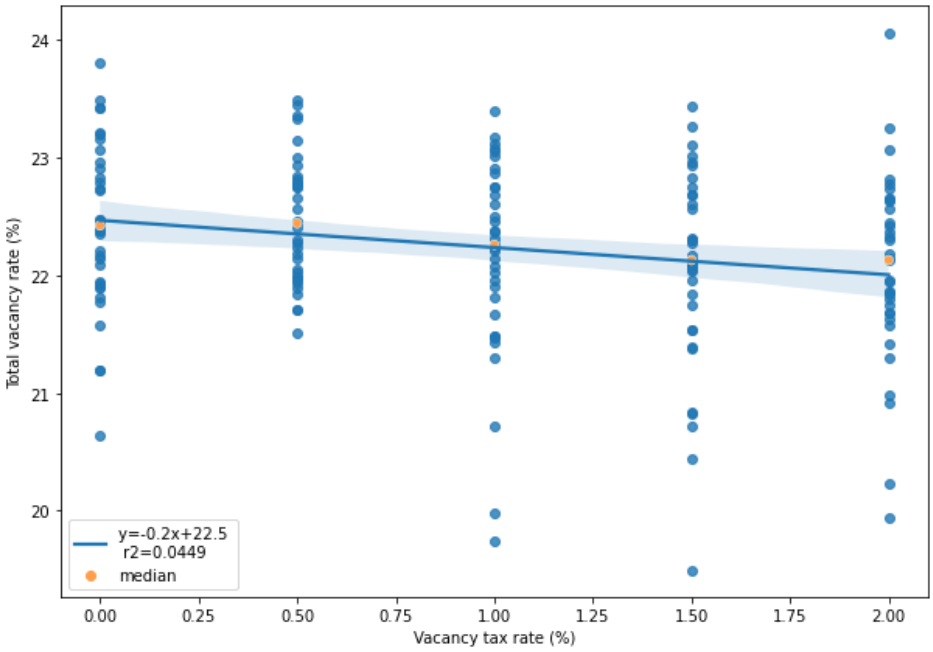

Figure 9 Combined vacancy tax rate (vacancy tax + property tax) and its effect on vacancy rate

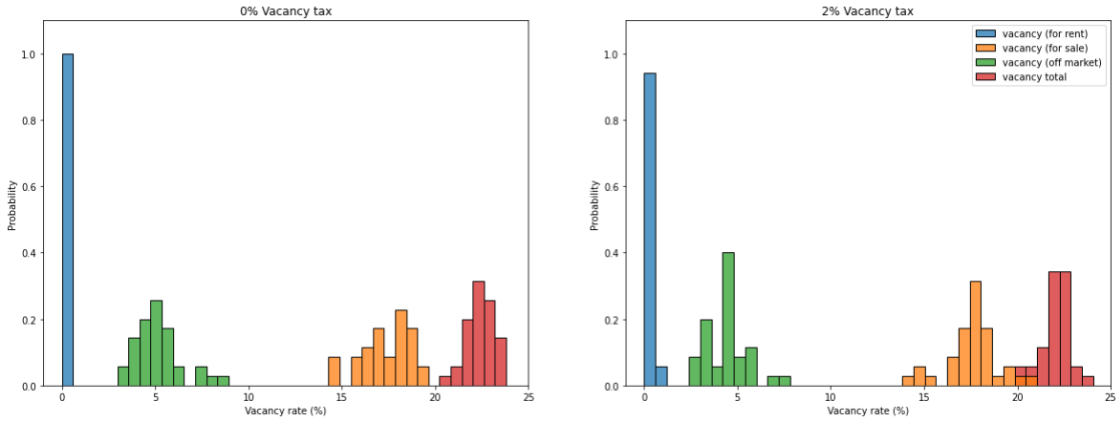

Figure 10 Frequency of each type of vacancy as at 0% and 2% vacancy tax

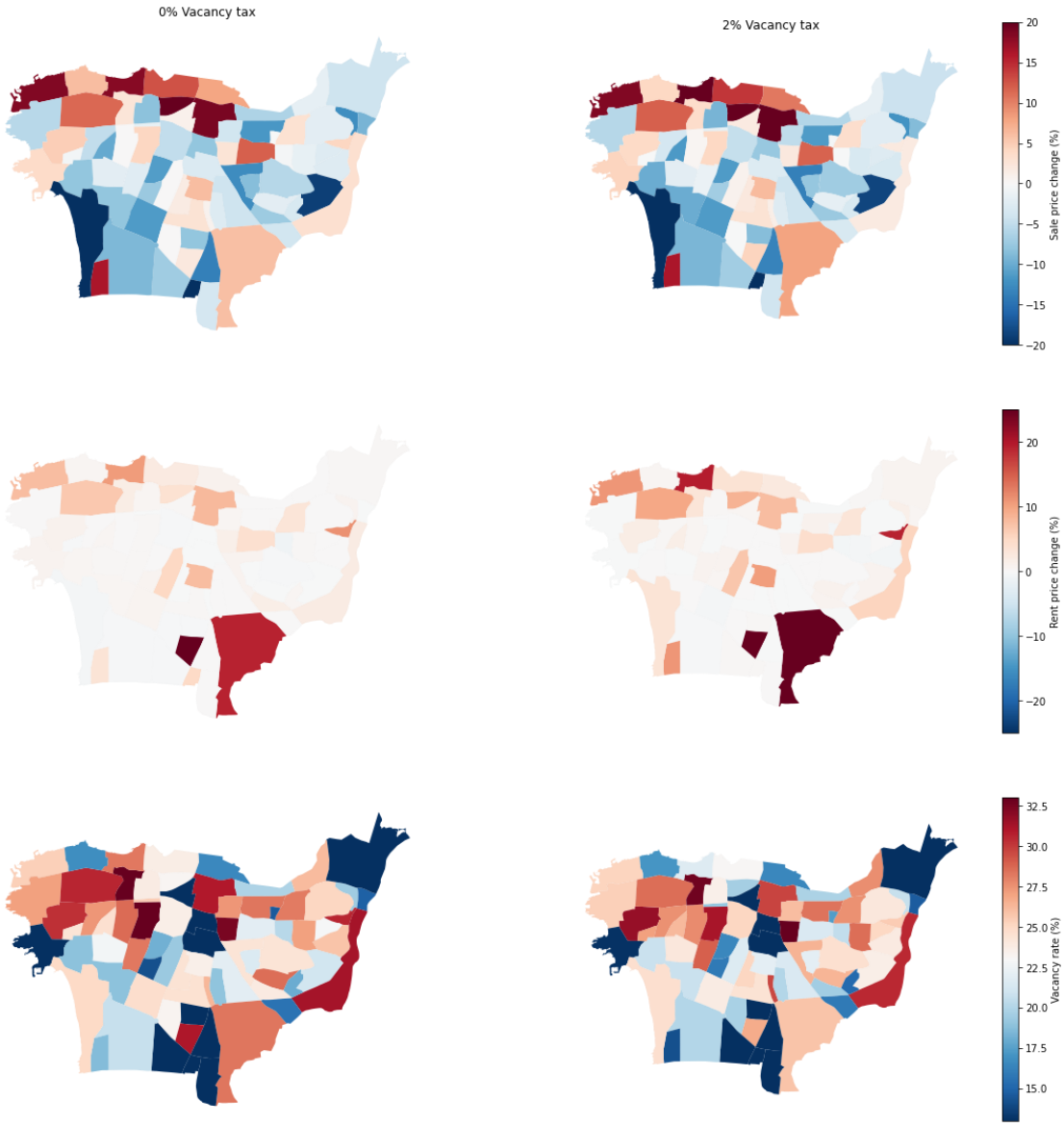

Figure 11 Spatially disaggregated mean change in sale and rental prices, and vacancy rates for the 0% and 2% vacancy tax clusters

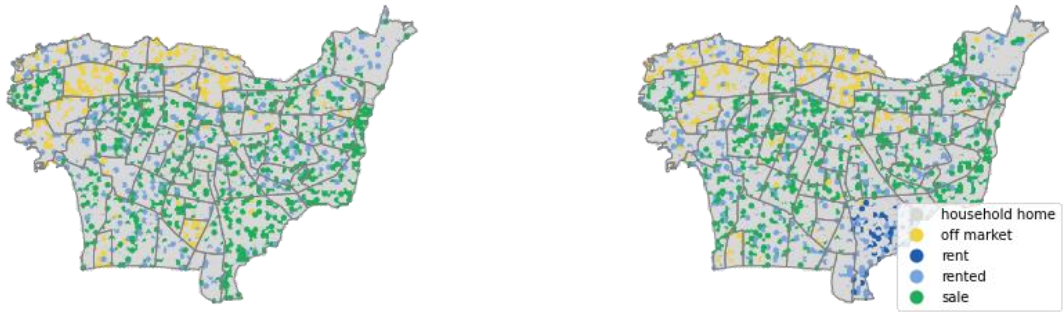

Figure 12 Comparison of tenure distribution of two sample future cities, at 0% (left) and 2% (right) vacancy tax rate

3.2.3. Scenario 2: The effect of alternative investment choices

The decision-making rules that investors follow when deciding whether to place their housing unit on the rental or sale market, or to hold it off the market, involves comparing the rate of return from waiting or renting to the rate of return from another alternative investment, which in this scenario was assumed to be a government bond with the Lebanese Central Bank. In an effort to understand the impact of this alternative investment on the vacancy rate, the interest rate from the central bank was varied between 1% and 12%, with increments of 1%. For each value, we generated 35 different future cities after 20 years of simulation. Figure 13 shows the output of this experiment. The correlation between the interest rate and vacancy rate was positive but not strong (0.234). Overall, the simulations indicated that for every 1% increase in the rate of return from the central bank bonds there was a 0.1% increase in the vacancy rate across the city.

The vacancy rate breakdown by the status of the property is shown in Figure 14. Similar to the previous scenario, the rental market vacancy was very low, and the sale market vacancy was the highest. In an effort to better understand these dynamics, we compared the city under two interest rates, namely a 2% and 12% interest rate. Notably, the vacancy rate in the rental market was higher on average under the 2% as compared to the 12% cluster. This can be attributed to two dynamics: first, as investors see a low interest rate from the Central Bank, they are encouraged to keep their investments on the housing market. As rates of return increase from alternative investments, less housing units are purchased and held by investors, as alternative investment strategies become potentially more profitable. Sale market vacancy rate also decreased in the 2%

cluster, as investors rush to deposit their money in a safe investment, such as real estate. This is a result consistent with observed patterns in Beirut (Fawaz & Zaatari, 2020).

To demonstrate the spatial effect that alternative investment choices have on the vacancy in the city, Figure 15 compares the mean price increases for rent and sale markets, and of vacancy rates under Central Bank interest rates of 2% and 12%. In the sale market, there was a differentiated effect on sale prices by neighbourhood. Areas, where prices decreased, did so at the same rate irrespective of the interest rate, whereas neighbourhoods that experienced an increase in price, saw a higher increase when the interest rate was set to 12% as compared to 2%. Interestingly, the same pattern did not appear for rental prices, indicating a divergence between rental prices and sale prices, a pattern observed globally in financialized housing markets (Hilber & Mense, 2021). Vacancy rates showed a correlation to sale prices as well, as vacancies increased in the neighbourhoods where sale prices increased the most.

Figure 16 shows tenure status between two sample future cities that developed under interest rates of 2% and 12%. The results clearly show that the expensive neighbourhoods of the city next to the northern waterfront exhibited a strong tendency to be hosts to speculative investment behaviour. Middle income neighbourhoods like Hamra and Badaro, had a relatively high vacancy rate under the 12% interest rate scenario, with many housing units remaining off the market. This can be attributed to rental prices being too low to entice the landlords to rent, while sale prices were comparatively high at initialization.

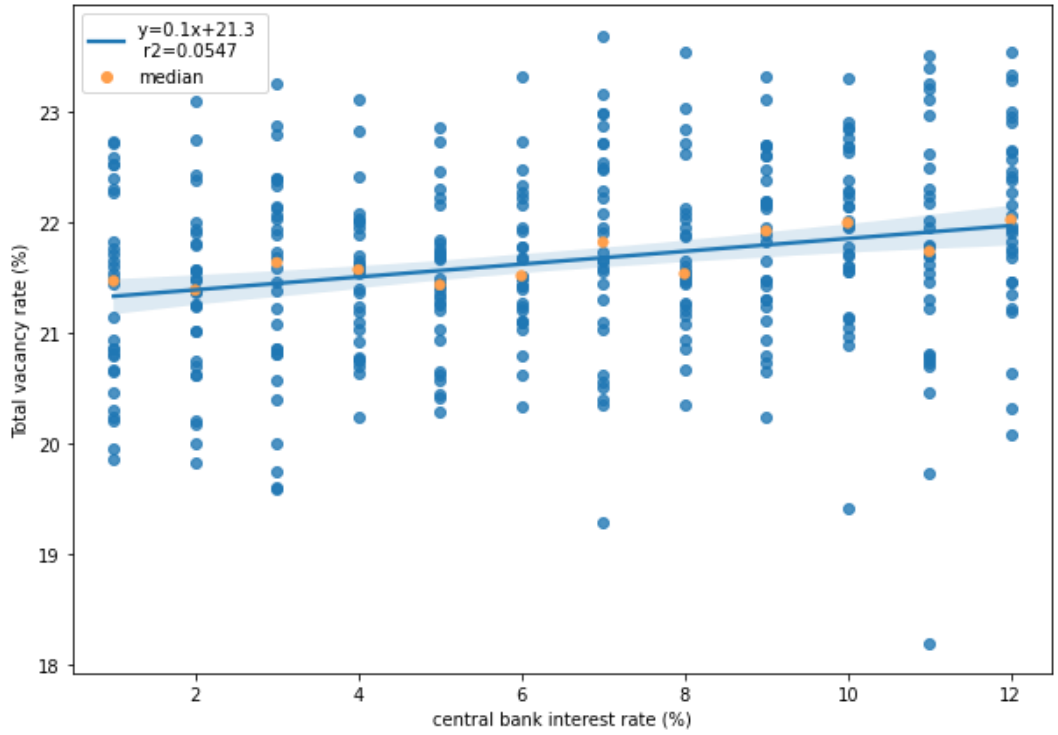

Figure 13 Effect of alternative investment rate of return on vacancy rate

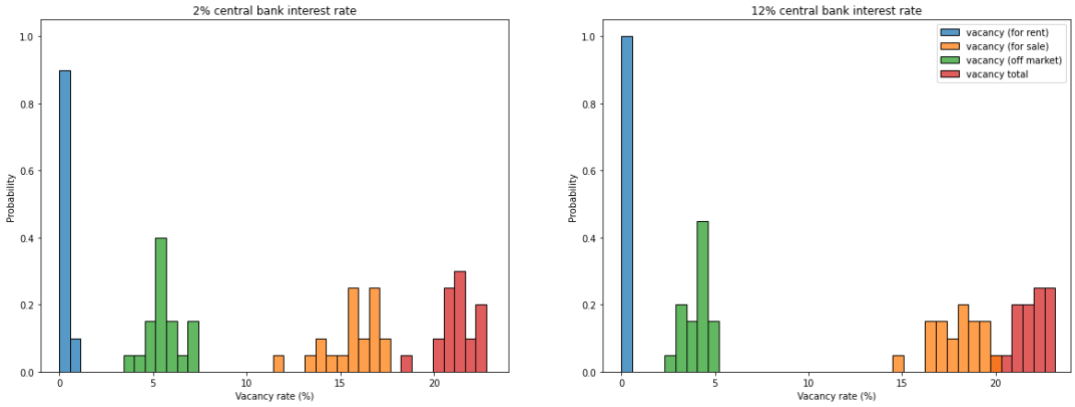

Figure 14 Probability of vacancy rate by type, split for 2% and 12% central bank interest rate

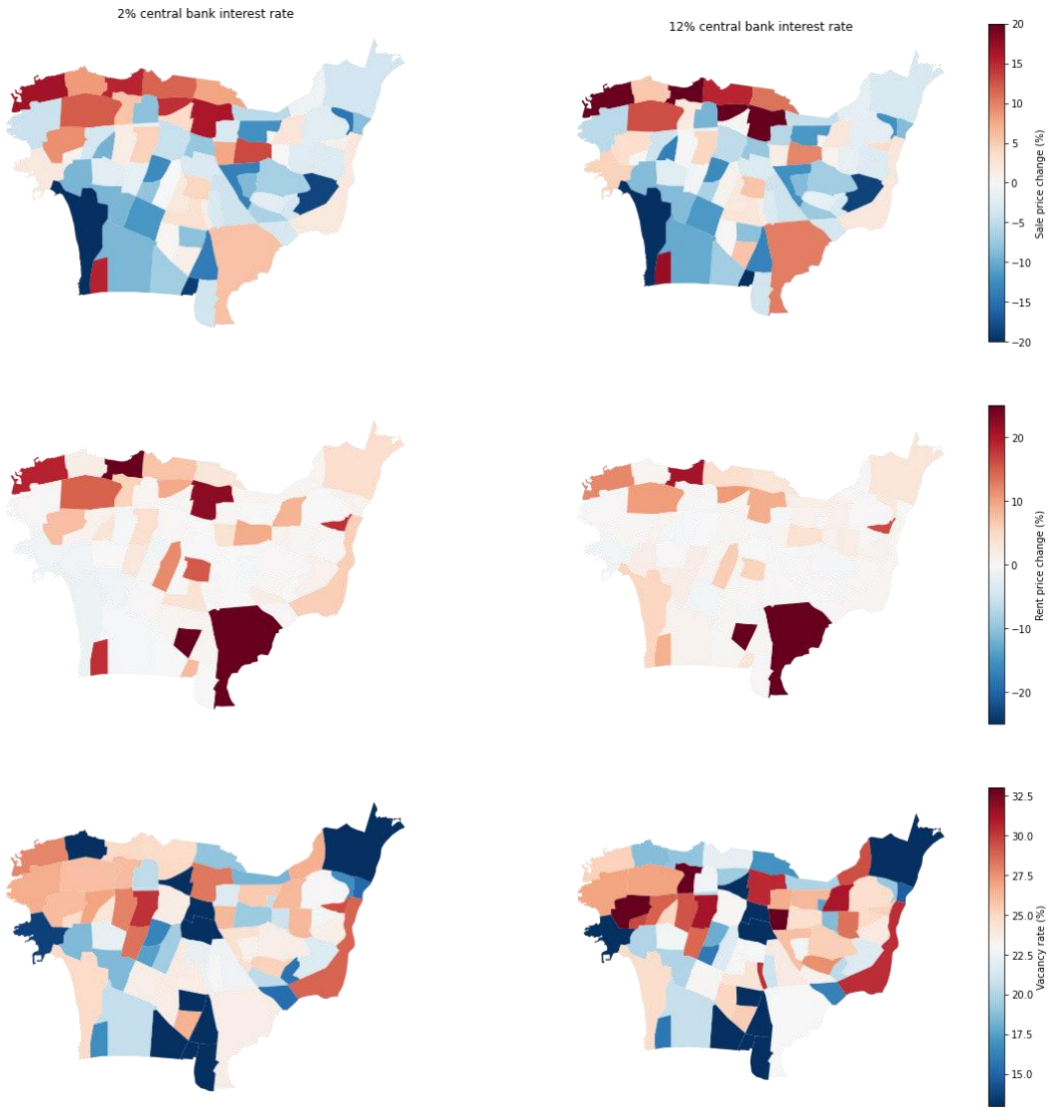

Figure 15 Spatially disaggregated mean vacancy rate for the 2% and 12% central bank interest rate clusters

Figure 16 Comparison of tenure distribution in at 2% (left) and 12% (right) rate of return from central bank bonds.

3.2.4. Scenario 3: The effect of increased demand

Another factor that drives vacancy rate is the level of demand for housing. Demand could be driven by many different factors, such as a family growing, a household splitting, rural to urban migration, an influx of refugees, change of average prices in the urban area, among many other possible factors. In this scenario, the mean number of new households arriving into the city each time step was increased from 6 new households per thousand housing units per year up to 16 per thousand. For each value, 35 possible future cities were generated. Figure 17 shows the variability in the vacancy as a function of the arriving number of housing units while holding the vacancy tax fixed to 2%. The results show that as demand increases by one new household per thousand units per time step, the vacancy rate decreased by 1.3%. The correlation between vacancy rate and housing demand was -0.92, indicating a very strong relationship.

A closer look at the vacancy by type is shown in Figure 18, for the two clusters of 7 and 13 new households arriving per thousand units per step. Similar to the pattern observed in scenario 1 the vacancy in the rental market was found to be consistently lower than that for sale. This may be interpreted to how the vacancy tax affects the rental market differently than the sale market, where rental prices stay relatively low, because they have to meet the housing budgets of tenants, while sale prices increase to meet speculative demand, resulting in higher vacancy rates. This is a pattern that has been observed worldwide, and it is particularly pronounced in “superstar” cities (Hilber & Mense, 2021).

In an effort to better understand the effects of a changing demand, I compared two sample future cities, one where demand was set to 7 new households per thousand units

per year, and another set at 13 per thousand units per year. The results are demonstrated in Figures Figure 18 and Figure 20. Figure 18 shows that with lower demand, the number of speculative investment housing units that are kept off-market was lower, while there was a higher vacancy rate in the sale market. This can be interpreted through the decision making of the investors, where with increased demand, unit prices increase more quickly, prompting more investors to hold on to their units while their prices increase.

Of note is the significant decrease in sale prices in some neighbourhoods of the city, even when the demand was high. This is likely to be due to housing budgets remaining constant, so sale prices had to decrease in order to meet demand, when households were unable to find housing in the neighbourhoods where prices have increased significantly. This was observed in the northern parts of the city.

Figure 19 shows the vacancy rate for the 7 and 13 new households per thousand units per step clusters. As expected, both sale and rental prices increased with increased demand. As for vacancy rates, the contrast is clear, where vacancies increased with lower demand, and decreased with higher demand. Interestingly, the expensive neighbourhoods were the exceptions to that rule, where speculative buying becomes the norm, driving up vacancy, as can be seen in the sample cities in Figure 20.

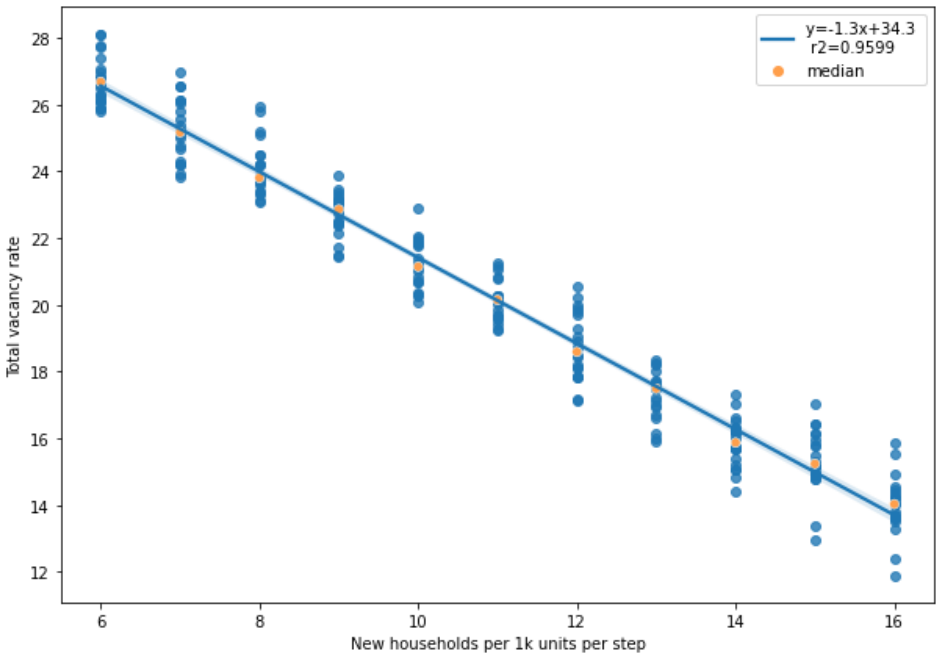

Figure 17 Effect of demand on vacancy rate

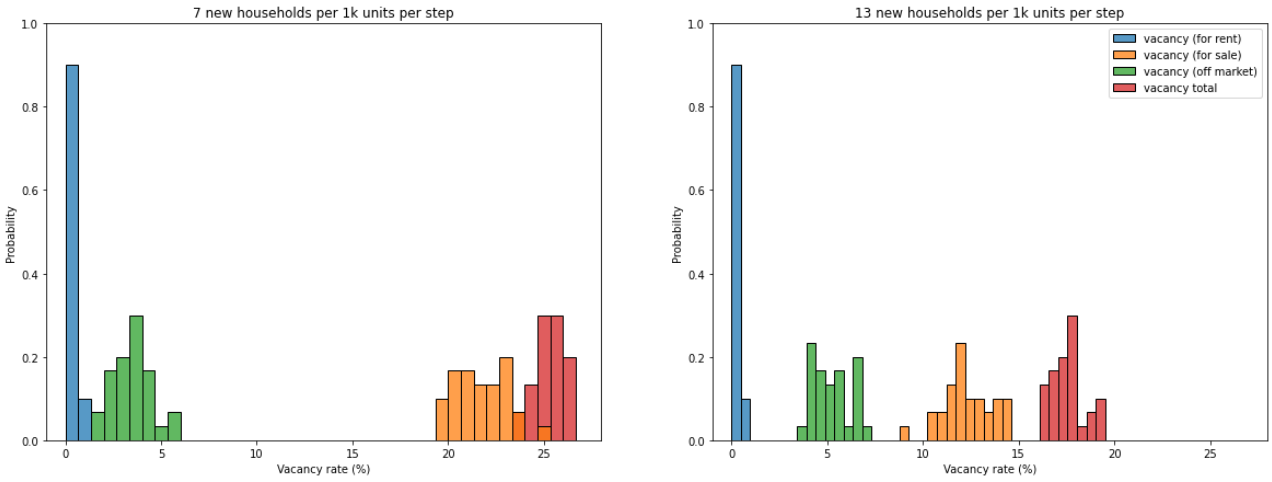

Figure 18 Probability of vacancy rate by type, split for 7 and 13 new households per 1k units per step

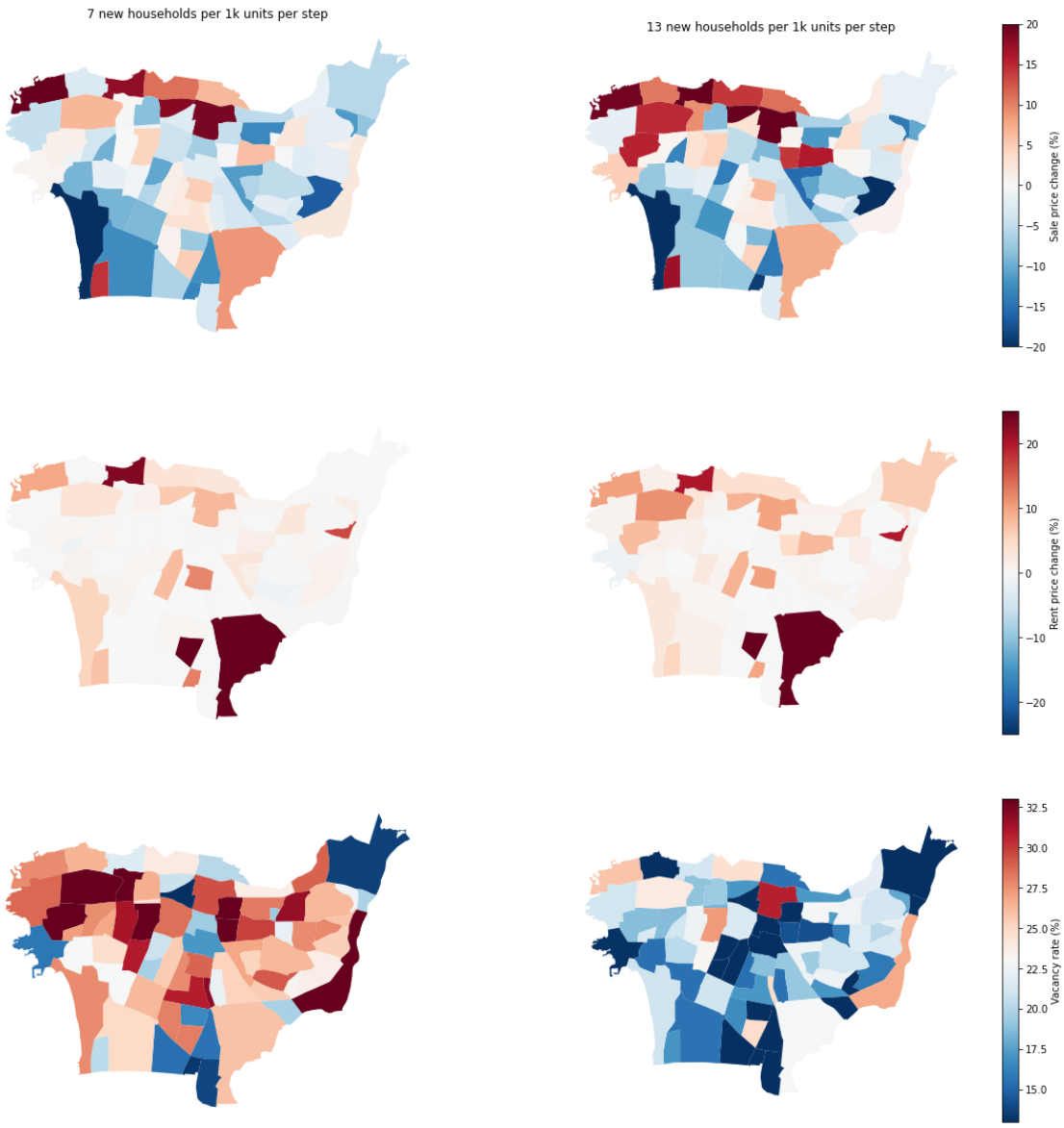

Figure 19 Spatially disaggregated mean vacancy rate for 7 and 13 new households per 1k units per step clusters

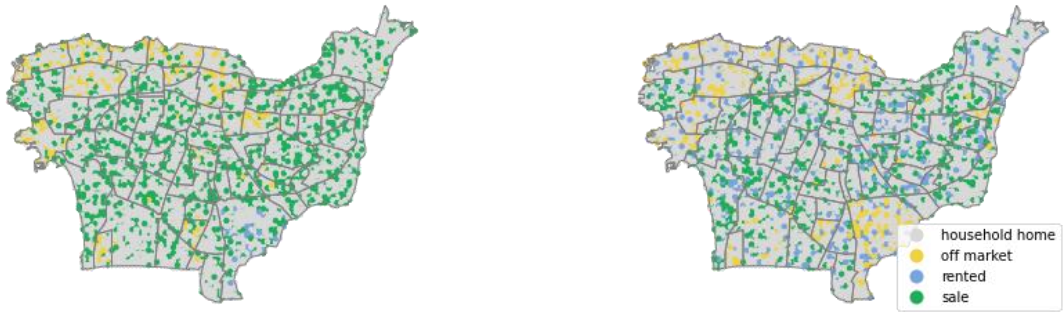

Figure 20 Comparison of tenure distribution in low (left) and high (right) demand scenarios

3.2.5. Scenario 4: The effect of changes in search duration

The final variable that was investigated was the number of housing units a household was willing to view while searching for a home. This was varied between 5 and 15 housing units to view per household. For each value, 35 possible future cities were generated, and their status compared after 20 years. Figure 21 shows the results of this scenario, where with each new housing unit that a household views, the vacancy rate fell by 0.1%, with a weak correlation between the two variables (-0.054). Figure 22 shows the breakdown of the vacancy rates by type, showing a consistent pattern to the previous scenarios.

Two future cities were compared in order to contrast the two extremes: one where households only viewed on average 6 housing units during their search, and another where they viewed 14 units, shown in Figure 23. Here, rent prices tended to increase, as households spend more time searching for housing units within their budget, with less regard for location. In general, vacancy rates increased slightly across the city. The quantity of sale and rental transactions increased when households spent more time searching for an appropriate housing unit, leading to a small, diffused effect on vacancy rate. As the effect of this variable was relatively weak, the differences between the scenarios were not as noticeable.

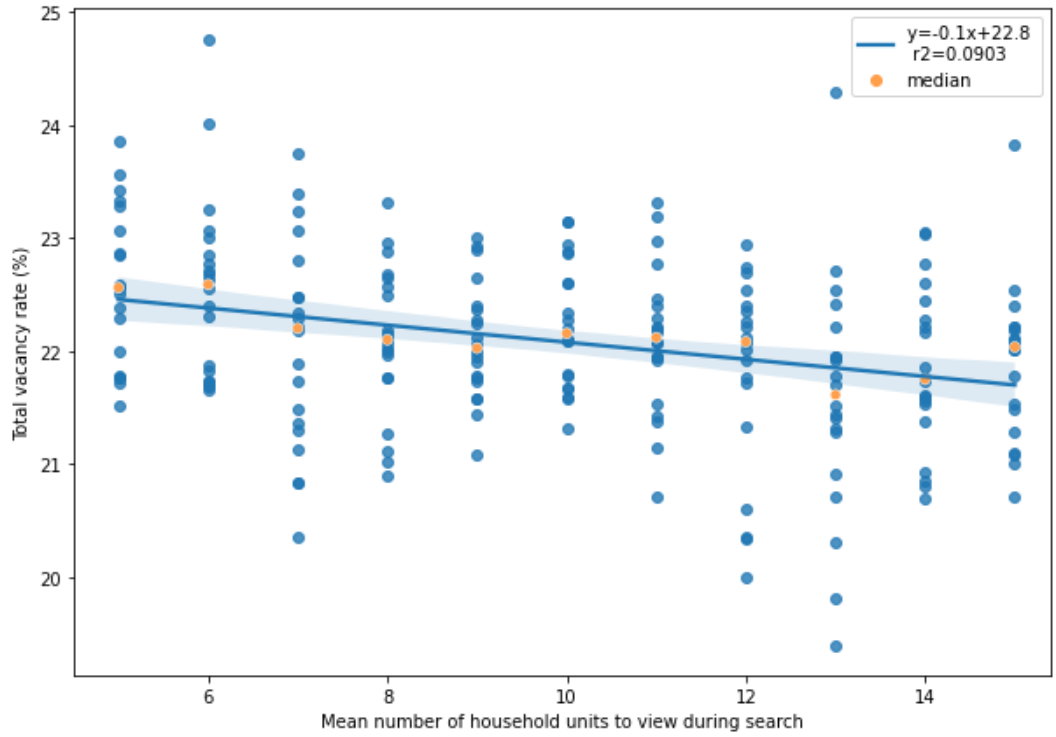

Figure 21 Effect of number of housing units viewed by a household on vacancy rate

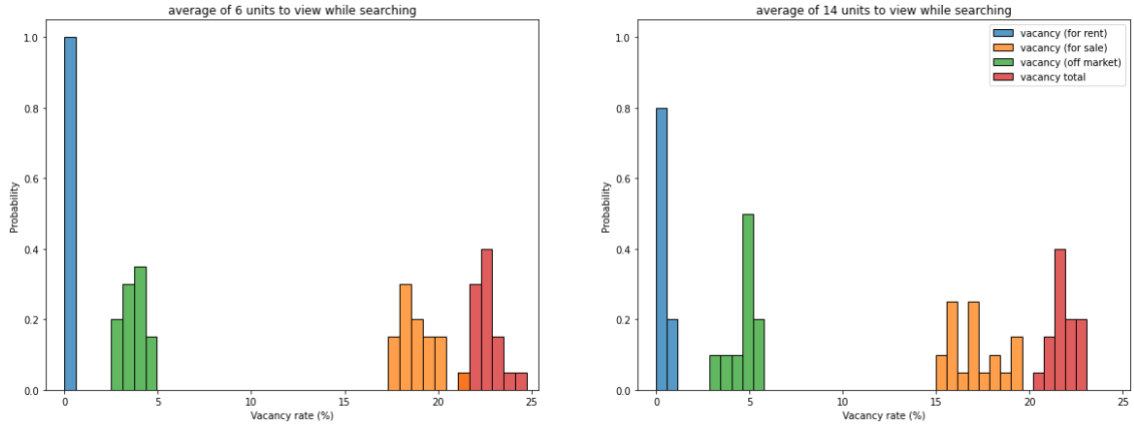

Figure 22 Probability of vacancy rate by type, split for 6 and 14 housing units viewed during search

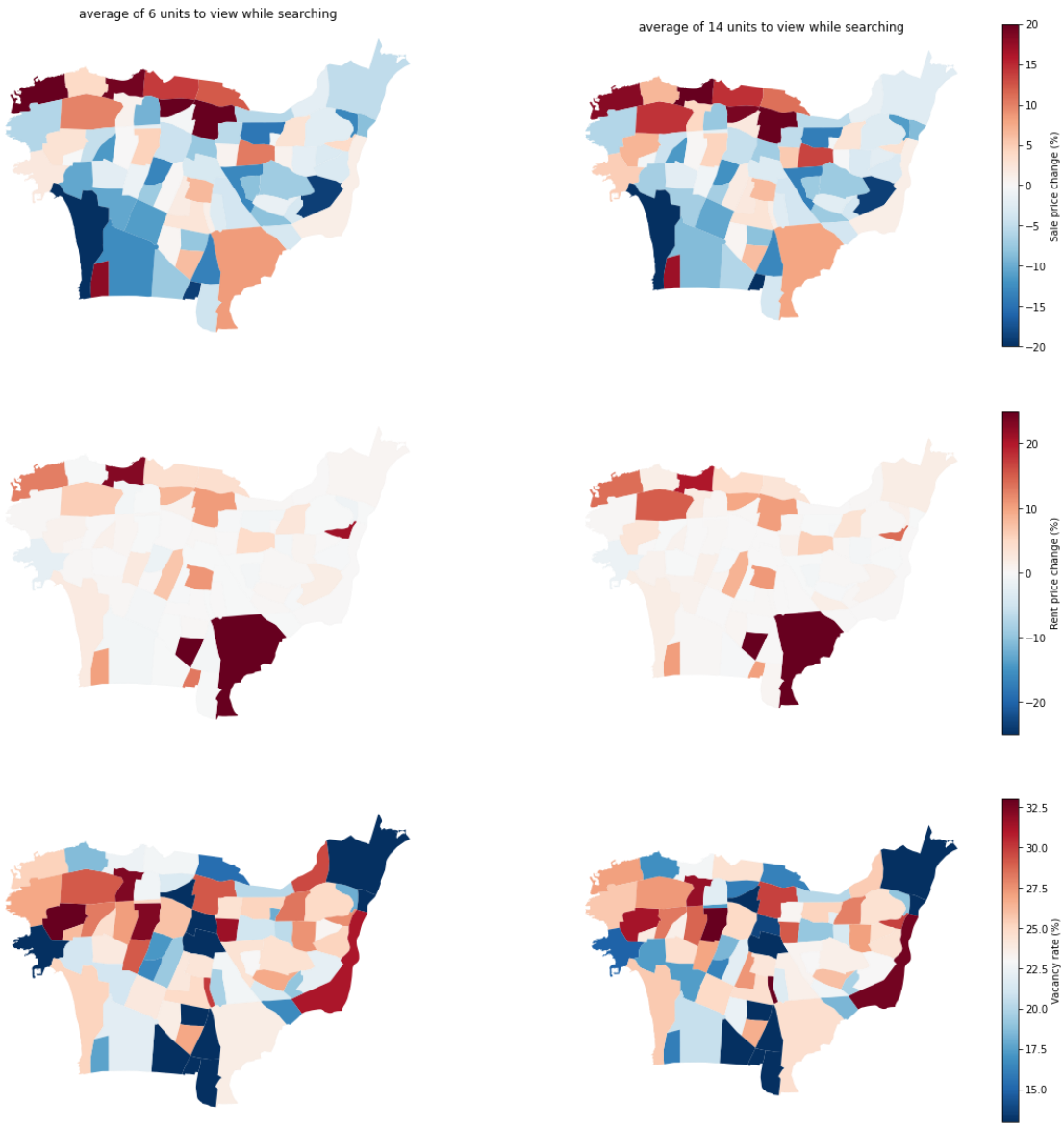

Figure 23 Spatially disaggregated mean vacancy rate for 6 and 14 housing units viewed during search

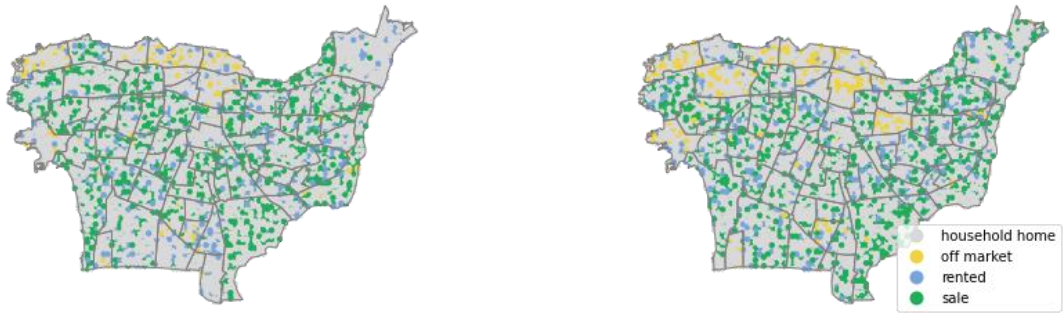

Figure 24 Comparison of tenure status when a household views 6 (left) and 14 (right) units during their search, on average.

3.3. Discussion

In this chapter, I demonstrated how the BSRI model can be applied to a city like Beirut, tuning the parameters to fit the city's characteristics and accommodating for the legal and economic environments in which it is situated in. Through this application, I explored four different scenarios, each of which examined the effects of parameters that were identified in the literature as having an important role on vacancy. These parameters were:

1) Vacancy tax
2) Demand for housing
3) Investment environment in the country
4) Length of time a household spends in their search for a housing unit

The increase of all of these variables decreased the vacancy rate in the city, with the exception for the investment environment, which when increased resulted also in a rise in the vacancy rate.

While the results of the model focused almost exclusively on the vacancy rates in the city, it is possible to use the model to examine other effects, such as income disparity of city residents, amount of tax revenue accumulated, and number of people leaving the city because of the unaffordability of the housing market. It is crucial to remember that this ABM was built for a specific purpose, which is to *describe* the effects of a vacancy tax on the housing market in a financialized housing paradigm. One missing component of the model is the effect of active housing policy by the state, which is very likely to produce different outcomes once integrated into the model dynamics. As such, for a vacancy tax policy to be complete, it has to be situated in a longer-term vision for the city. It must also recognize the use value of housing as

distinct to its exchange value, and respond to the dynamic evolution of the city as circumstances evolve. For example, municipal revenues from the leveed vacancy tax have to be dedicated to support the establishment and expansion of an affordable housing stock in the city. This can take the form of providing facilitated loans to housing cooperatives, buying housing stock and renting it at affordable prices, or upgrading informal settlements.

CHAPTER 4

CONCLUSION
WHAT CAN WE LEARN FROM THIS EXPERIMENT?

4.1. Summary

Through this thesis, I sought to review the literature positioning vacancy as an important indicator of the health of the housing sector, particularly in Beirut. Vacancy is affected by various factors, including demand on housing, the stock of housing available, the length of time a household spends searching for a housing option, and the investment environment in the country, among other factors. Hence, a vacancy tax is a policy proposal that policy makers are advocating for, with the aim of reducing the vacancy rate in the financialized housing market, and to prioritize the use value of housing over its exchange value.

However, the housing market is a complex system, and interventions have possible unforeseen consequences. Thus, policy makers make use of spatial decision support systems in order to explore the parameters of the system and understand their effects on under various what-if scenarios. Those decision support systems fit into models of learning about complex systems, where a “virtual world” is required that assists policy makers in gaining a deeper understanding of the systems they seek to intervene in.

Among the different modelling paradigms, agent-based modelling is particularly suitable to market models, as it integrates learnings from both qualitative research and quantitative research. It allows for the discovery of emergent behaviours in a complex

system. ABMs also integrate with the established practices of urban planning. They also allow for participatory processes, where the model acts as the “boundary object” between various stakeholders, thus contributing to restoring the depleted democratic governance processes in the region.

Through this thesis, I proposed a design for an ABM, which describes the effect of a vacancy tax on a financialized housing market. I used pattern-oriented modelling method, where I captured the structure of the model by integrating patterns observed at various scales in the city. In particular, I captured the sale and rental price distribution, the neighbourhood-specific differentiation in patterns, and vacancy patterns across the city. I also captured the process flow, exchange, and circulation of ownership of housing units between households and investors. Additionally, I captured the process of investors using housing units as safety-deposit boxes for their surplus capital. Finally, I described the process of new households entering the market, as well as households leaving the market after failing to find suitable housing over time. Importantly, the model did not account for patterns of communal or political affiliation. I used the Overview, Design concepts, Details + Decision (ODD+D) making protocol to describe the model, allowing other researchers to reproduce it.

I then applies the model to the case of Beirut, a city that has a 23% vacancy rate, which has been attributed in the literature to the financialization of its housing market. I calibrated the model with empirical data from the Beirut Urban Lab and Ramco Real Estate Advisors, and ran it in four different scenarios, testing the parameters known to affect the vacancy rate. These included: 1) introducing a vacancy tax; 2) increasing the rate of return from alternative investment options; 3) increasing demand; and 4) increasing the search time for housing by households.

Of the four scenarios, the strongest effect was that of increased demand, where vacancy rates decrease significantly across the city. The correlation values for each of the scenarios are -0.2119, 0.2339, -0.9815, and -0.0537 respectively. The model captured many of the observed phenomena in the literature about housing markets, including the pattern of investors keeping housing units off the market in higher-income neighbourhoods. Additionally, lower-income neighbourhoods tended to have lower vacancy rates after 20 years than middle- and higher-income neighbourhoods. The model was affected by households' preferences for proximity to selected locations in the city, which affected the vacancy rates as well as sale and rental prices in locations that are farther from those locations. It is hoped that policy design utilizing vacancy rates are able to observe these patterns and identify the levers through which they can best impact their city.

4.2. Further research questions

Through the process of constructing and examining the output of the model, many old questions resurface, and new questions arise (Smaldino et al., 2015). Below I summarize some of the questions that arose through my research.

4.2.1. Theoretical framework

This model captures the dynamics of a financialized housing market. How could the model be adjusted to include more of the non-financial aspects of the value of land?

There are new approaches to mapping intractable conflicts. For example, Homer-Dixon et al (2014) used cognitive affective mapping to capture the relationship between psychological processes and logical processes. Can using this methodology substitute

for prospect theory in the model? Can it be used to adapt the model for other housing-related conflicts in the city, such as the conflict between old landlords and old tenants?

How does the model behave under different theoretical approaches to decision making? Does prospect theory capture the dynamics better than expected value or wealth optimisation algorithms? Given that the application of prospect theory assumes knowledge of the probabilities in each outcome, can those probabilities be calculated differently?

What is the relationship between rental prices and sale prices? How do investors determine their asking prices? How do households formulate their bid price? How are those prices matched and settled? In this model, I used basic versions of each of those mechanism, but those could be improved with more targeted research. For example, a hedonic price model could help determine the utility function for each household and better specify the asking prices of investors. Additionally, the "stopping time problem" implemented in the model in the satisficing process for selecting bids by investors is a simplistic implementation. What would be a better decision-making rule in this case? We know that some investors specialize in specific neighbourhoods and market segments. How does that affect the vacancy rates in the city? Since the demand for housing has the strongest effect on vacancy rates, what kind of effect does supply have? How do developers decide on the locations where to build?

Households arriving in the city do not currently differ in their proximity preferences. Can we create archetypes of different households, and see how the model reflects their preferences? Does their location preference translate into elasticity in their housing budget? Households currently sample units to view based solely on their housing budgets, but what if they also used sectarian affiliation in their sampling?

Would that create a segregation pattern similar to that described by the Schelling model? Do households use a different utility function when they are renting, as opposed to when they are seeking to purchase a home? How can we include communal and political affiliations? How do these factors affect the bid matching process between buyers and investors?

4.2.2 Empirical data

The model currently uses Cartesian distance to calculate proximity to specific centres in the city and to weight the utility of the new incoming households. Would using road network distance change the outputs of the model? The distribution of housing units is currently uniform across the city, without accounting for density differences. It is possible to integrate data collected by the Beirut Urban Lab to reflect the density of neighbourhoods more accurately. The same data can also be used to capture the increased supply of housing, by extrapolating from building permit data already recorded. The parameters used to calibrate prospect theory in the BSRI model were calibrated loosely. One wonders about the model's sensitivity to these values and if it can allow these parameters to fluctuate over time, and in response to market conditions?

Neighbourhood definition in the current model was drawn along infrastructural lines and data from a real estate company. Neighbourhood definition is a contentious issue (Fawaz et al., 2018). This is a sign that they are an emergent phenomenon. Can we explore the emergence of neighbourhoods using ABMs? How does neighbourhood definition affect neighbourhood prices? Currently, each neighbourhood's trend was estimated separately, and effects did not "spill over" along neighbourhood boundaries.

How would “fuzzy” neighbourhood boundaries affect the price evolution in the model? Are informal neighbourhoods affected by financialization differently from other neighbourhoods?

4.2.3. Better visualization

To be able to extract more insights from the model, users need to easily switch between different levels of abstractions. For that, different visualizations must be readily available, capturing different parameters and dimensions of the model. For example, a visualization of how long housing units stay on the market, aggregated by neighbourhood is an important addition to the model in the future.

4.2.4 Speculative scenarios

The model currently does not respond to cataclysmic events, such as the loss of a significant portion of the housing stock due to an explosion, or the massive influx of new households, or to the precipitous drop in rates of return from other sectors in the economy. Would the model successfully capture the effects of such events? Moreover, the model was not used to explore the effects of the increased prevalence of short-term rental units (such as AirBnB) on the sale and rental prices in the city nor on the vacancy rates. Finally, the model currently assumes a uniform tax on all housing units, regardless of their price. How would a progressive tax scheme affect the city differently?

APPENDIX

ODD + D protocol for the BSRI model

Outline (→ template)		**Guiding questions**	**Own ODD+D Model description**
Overview	I.i Purpose	I.i.a What is the purpose of the study?	To describe the market dynamics of a financialized housing market, through examining the efficacy of a vacancy tax under different circumstances. Propose a ABMs as an additional tool for urban planners in the Levant
		I.ii.b For whom is the model designed?	Urban planners, policy makers, urban activists
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	Agents/individuals: Households, investors, realtors Spatial units: housing units
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	Households: budget, interest rate, down payment, actual price preferences for locations, preferences for amenities, units to view during search. Investors: housing units owned, interest rate, loan size, subjective discount factor, loss aversion factor, probability weighting. Realtors: neighbourhood, rent/sale history of neighbourhood, transaction history. Housing units: sale/rent price, sale/rent asking price, location, condition, amenities, operating costs, distance from specified locations.
		I.ii.c What are the exogenous factors / drivers of the model?	Legal minimum contract length. Investment environment for alternative investments.
		I.ii.d If applicable, how is space included in the model?	Space is included in the spatial distribution of housing units, divided into neighbourhoods controlled by realtors
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	The rasterized version of the model has a 100x100, settable by the user, equivalent to 50x70m blocks. Each time step is equivalent to 1 year.
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	See Figure 3

Design Concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	Financialization of housing
		II.i.b On what assumptions is/are the agents' decision model(s) based?	Bounded rationality of investors, realtors, and households Loss aversion by investors, using prospect theory Utility maximization by households while searching for housing units
		II.i.c Why is a/are certain decision model(s) chosen?	Prospect theory to allow for evaluation of alternative investments while accommodating for non-financial aspects of decision making, including loss aversion.
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	Ramco Real Estate Advisers for the asking prices per neighbourhood Beirut Urban Lab Built Environment Database for vacancy rates
		II.i.e At which level of aggregation were the data available?	Aggregation for vacancy rate is done at the city level. Asking prices are aggregated at the neighbourhood level
	II.ii Individual Decision Making	II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included?	Each investor decide on placing each housing unit they own on either the rental or sale market, at a specific asking price. Otherwise, to hold it off the market. Each household samples a number of housing units to view, evaluate their utility, and bid on. Each investor decides on a bid from the bids received, in sequential order, and decides on a settled price.
		II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	Investors maximize the subjective utility for their investments Households maximize their subjective utility within their price range
		II.ii.c How do agents make their decisions?	Investors make their decision based on the decision tree described in Figure 7.

			Households make their decisions based on their utility function.
		II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	Investors adapt their asking price based on the market conditions (given by the realtor). Investors decide on placing their units on the sale or rental market based on the exogeneous investment environment.
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	Investor decisions are weighed by the probability of the outcomes of their choices. The probability weighing in prospect theory is subjective, and is proxy for susceptibility to anecdotal evidence about market conditions.
		II.ii.f Do spatial aspects play a role in the decision process?	Investors decide on the asking price based on the neighbourhood a housing unit is located in. Households evaluate the utility of a housing unit partially based on its location.
		II.ii.g Do temporal aspects play a role in the decision process?	Neighbourhood price trends are based on the past three time steps, weighed more heavily for the most recent year. Investors evaluate bids in the order received, but they lose 1% of their optimism with every unsuitable bid they evaluate.
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	Weighing probabilities of the outcomes in prospect theory is accommodating for uncertainty and lack of knowledge of the market.
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?	Investors learn that their probability of finding a suitable bid decreases with each bid they evaluate, thus decreasing their optimism factor.
		II.iii.b Is collective learning implemented in the model?	No
	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?	Investors sense the market conditions from the realtors, and the rate of return on alternative investments from the exogeneous variable set by the user. Realtors set the average prices based on the transactions they record in their ledger. All quantities are sensed precisely.
		II.iv.b What state variables of which other individuals can an individual perceive? Is	Households and investors do not sense the state variables of other households or investors.

		the sensing process erroneous?	
		II.iv.c What is the spatial scale of sensing?	Sensing market conditions happens on the neighbourhood scale. Sensing the alternative investment rate of return is model-wide.
		II.iv.d Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?	Investors gather market conditions by asking the realtor directly. They are assumed to know the alternative investment rate of return.
		II.iv.e Are costs for cognition and costs for gathering information included in the model?	Households have a limited capacity to view housing units, so they view a maximum of number of units set at initialization, with a mean set by the user.
	II.v Individual Prediction	II.v.a Which data uses the agent to predict future conditions?	Investors use historical neighbourhood asking prices from realtors to set their asking price for the next year.
		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	When setting an asking price, investors price is multiplied by a subjective optimism factor, ranging between [0.95, 1.05]
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?	Subjective optimism factor introduces erroneous prediction for market prices.
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	Interactions are direct between investors and households. Investors interact with each other indirectly, as their settled bids affect the final prices recorded in the realtor's ledger, thus affecting the asking price of other investors in the next time step.
		II.vi.b On what do the interactions depend?	Investor-household interaction depend on the budget that a household has for housing, affecting which neighbourhood they seek housing in. Realtors mediate the interaction between investors.
		II.vi.c If the interactions involve communication, how are such communications represented?	No communication involved.

		II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?	No coordination networks exist.
	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?	No.
		II.vii.b How are collectives represented?	Not applicable.
	II.viii Heterogeneity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?	Investors are either corporate or amateur. Details in Table 2 Households differ in their attributes, as shown in Table 3.
		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	Households make their decision based on whether they are a buyer, renter, or an owner. Investors decision making process is identical for amateur and corporate investors, but they differ in the parameters used, thus producing different outcomes.
	II.ix Stochasticity	II.ix.a What processes (including initialization) are modeled by assuming they are random or partly random?	During initialization, every aspect of the model is initialized randomly. This includes, the distribution of housing units between investors and owners, the types of investors, the types of households, and the types of tenure. Households and investors attributes are assigned randomly based on appropriate distributions, with the parameters set by the model's user.
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?	Vacancy rate, broken down by rent, sale, and off-market. Budget distribution of seekers, for both rent and sale. Asking prices distribution for both rental and sale market. Counts of unhoused households, and households that leave the city, and their budgets. Housing budgets of the current residents of the city. Average asking prices per neighbourhood.

		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	A spatial pattern of investment, where housing units in expensive neighbourhoods stay off-market, while in middle class neighbourhoods they are on the sale market.
Details	II.i Implementation Details	III.i.a How has the model been implemented?	Using Mesa, written in Python.
		III.i.b Is the model accessible and if so where?	Code is available at https://gitlab.com/majdal/beirut-agent-based-modelling Licensed under the Anti-Capitalist Software License (version 1.4)
	III.ii Initialization	III.ii.a What is the initial state of the model world, i.e. at time t=0 of a simulation run?	Housing units are created according to the dimensions of the grid set by the user. Housing unit prices are set according prices per neighbourhood. Housing units are assigned to neighbourhoods using the neighbourhood boundary file provided. Each housing unit is assigned a tenure type. Those are: Owned by and lived in by household, or owned by an investor. Investment units are either currently rented, on the sale market, on the rental market, or held off-market. Some households are already in the city searching for housing.
		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	Every initialization gives a new distribution.
		III.ii.c Are the initial values chosen arbitrarily or based on data?	Neighbourhood boundaries are modified on Electricité du Liban districts. Asking prices per neighbourhood are based on Ramco Real Estate Advisors data from 2015, 2017, and 2018. Vacancy rates are from the Beirut Urban Lab Built Environment Database project.
	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?	Neighbourhood boundaries file, which includes asking prices per meter squared per neighbourhood.
	III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes	Decision making by investors Bid price setting by households

		listed in ‘Process overview and scheduling’?	
		III.iv.b What are the model parameters, their dimensions and reference values?	See Tables Table 3, Table 4, Table 5, and Table 10
		III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	See section 2.3.3.

REFERENCES

Aalbers, M. B. (2017). The Variegated Financialization of Housing. *International Journal of Urban and Regional Research*, *41*(4), 542–554. https://doi.org/10.1111/1468-2427.12522

Aalbers, M. B., & Gibb, K. (2014). Housing and the right to the city: Introduction to the special issue. *International Journal of Housing Policy*, *14*(3), 207–213. https://doi.org/10.1080/14616718.2014.936179

Aalbers, M. B., Rolnik, R., & Krijnen, M. (2020). The Financialization of Housing in Capitalism′s Peripheries. *Housing Policy Debate*, *30*(4), 481–485. https://doi.org/10.1080/10511482.2020.1783812

Abou-Ibrahim, H. (2021). *Housing Production at a Moment of Financialization, a Case Study from the Suburbs of Beirut*. American University of Beirut.

Armstrong, M. P., Densham, P. J., & Rushton, G. (1986). *Architecture for a microcomputer based spatial decision support system*. 13.

Arnott, R. (1989). Housing vacancies, thin markets, and idiosyncratic tastes. *The Journal of Real Estate Finance and Economics*, *2*(1), 5–30. https://doi.org/10.1007/BF00161714

Arthur, W. B. (1999). Complexity and the Economy. *Science*, *284*(5411), 107–109. https://doi.org/10.1126/science.284.5411.107

Arthur, W. B., Durlauf, S., & Lane, D. A. (2014). Process and the emergence in the economy. *The Economy as an Evolving Complex System II*.

Ashkar, H. (2015). Benefiting from a Crisis: Lebanese Upscale Real-Estate Industry and the War in Syria. *Confluences Mediterranee*, *N° 92*(1), 89–100.

Beckmann, M. J. (1969). On the distribution of urban rent and residential density. *Journal of Economic Theory*, *1*(1), 60–67. https://doi.org/10.1016/0022-0531(69)90012-X

Bekdache, N. (2015). Evicting Sovereignty: Lebanon′s Housing Tenants from Citizens to Obstacles. *The Arab Studies Journal*, *23*(1), 320–350.

Belsky, E. S. (1992). Rental vacancy rates: A policy primer. *Housing Policy Debate*, *3*(3), 793–813. https://doi.org/10.1080/10511482.1992.9521110

Blomley, N. (2008). Simplification is Complicated: Property, Nature, and the Rivers of Law. *Environment and Planning A: Economy and Space*, *40*(8), 1825–1842. https://doi.org/10.1068/a40157

Buckley, R. M., & Kalarickal, J. (2006). *Thirty Years of World Bank Shelter Lending: What Have We Learned?*

Chattoe-Brown, E. (2013). Why Sociology Should Use Agent Based Modelling. *Sociological Research Online*, *18*(3), 31–41. https://doi.org/10.5153/sro.3055

City of Toronto. (2020, December 3). *City of Toronto recommends a tax on vacant homes in Toronto* (Toronto, Ontario, Canada). City of Toronto; City of Toronto. https://www.toronto.ca/news/city-of-toronto-recommends-a-tax-on-vacant-homes-in-toronto/

Credit Suisse. (2019). *Global Wealth Report 2019* (Global Wealth Report). Credit Suisse. https://www.credit-suisse.com/about-us/en/reports-research/global-wealth-report.html

Crooks, A. T., & Heppenstall, A. J. (2012). Introduction to Agent-Based Modelling. In A. J. Heppenstall, A. T. Crooks, L. M. See, & M. Batty (Eds.), *Agent-Based*

Models of Geographical Systems (pp. 85–105). Springer Netherlands. https://doi.org/10.1007/978-90-481-8927-4_5

de Castro, P. A. L., Barreto Teodoro, A. R., de Castro, L. I., & Parsons, S. (2016). Expected utility or prospect theory: Which better fits agent-based modeling of markets? *Journal of Computational Science*, *17*, 97–102. https://doi.org/10.1016/j.jocs.2016.10.002

Doyle, K. (2015). Facebook, Whatsapp and the commodification of affective labour. *Communication, Politics & Culture*, *48*(1), 51.

Edmonds, B., Le Page, C., Bithell, M., Chattoe-Brown, E., Grimm, V., Meyer, R., Montañola-Sales, C., Ormerod, P., Root, H., & Squazzoni, F. (2019). Different Modelling Purposes. *Journal of Artificial Societies and Social Simulation*, *22*(3), 6.

Epstein, J. M. (1999). Agent-based computational models and generative social science. *Complexity*, *4*(5), 41–60. https://doi.org/10.1002/(SICI)1099-0526(199905/06)4:5<41::AID-CPLX9>3.0.CO;2-F

Fawaz, M. (2009). Neoliberal Urbanity and the Right to the City: A View from Beirut′s Periphery. *Development and Change*, *40*(5), 827–852. https://doi.org/10.1111/j.1467-7660.2009.01585.x

Fawaz, M. (2017). *Urban Policy: A Missing Government Framework*. Lebanese Centre For Policy Studies. http://lcps-lebanon.org/featuredArticle.php?id=116.

Fawaz, M., Garbieh, A., Harb, M., Salamé, D., American University of Beirut, & Issam Fares Institute for Public Policy and International Affairs. (2018). *Refugees as city-makers*.

Fawaz, M., Salamé, D., & Serhan, I. (2017). *You Can Stay in Beirut, Towards Inclusive Urban Housing Policies* (Policy Brief No. 8; p. 8). AUB Policy Institute.

Fawaz, M., & Zaatari, A. (2020). *Property Tax: No More Vacancy Exemptions*. http://lcps-lebanon.org/featuredArticle.php?id=319

Fieguth, P. (2017). Systems Theory. In P. Fieguth (Ed.), *An Introduction to Complex Systems: Society, Ecology, and Nonlinear Dynamics* (pp. 13–39). Springer International Publishing. https://doi.org/10.1007/978-3-319-44606-6_3

Filatova, T., Parker, D., & van der Veen, A. (2009, January 31). *Agent-Based Urban Land Markets: Agent′s Pricing Behavior, Land Prices and Urban Land Use Change* [Text.Article]. http://jasss.soc.surrey.ac.uk/12/1/3.html

Filatova, T., Voinov, A., & van der Veen, A. (2011). Land market mechanisms for preservation of space for coastal ecosystems: An agent-based analysis. *Environmental Modelling & Software*, *26*(2), 179–190. https://doi.org/10.1016/j.envsoft.2010.08.001

Forrest, R., & Williams, P. (1984). Commodification and Housing: Emerging Issues and Contradictions. *Environment and Planning A: Economy and Space*, *16*(9), 1163–1180. https://doi.org/10.1068/a161163

Frigg, R., & Hartmann, S. (2018). Models in Science. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy* (Summer 2018). Metaphysics Research Lab, Stanford University. https://plato.stanford.edu/archives/sum2018/entries/models-science/

Garcia, B., Jiménez, E., Jones, G., & Ward, P. (1994). Social agents in land and property development. *Methodology for Land and Housing Market Analysis*, 88–101.

Geanakoplos, J., Axtell, R., Farmer, J. D., Howitt, P., Conlee, B., Goldstein, J., Hendrey, M., Palmer, N. M., & Yang, C.-Y. (2012). Getting at Systemic Risk via an Agent-Based Model of the Housing Market. *American Economic Review*, *102*(3), 53–58. https://doi.org/10.1257/aer.102.3.53

Giddens, A. (1984). *The constitution of society: Outline of the theory of structuration*. Univ of California Press.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S. K., Huse, G., Huth, A., Jepsen, J. U., Jørgensen, C., Mooij, W. M., Müller, B., Pe′er, G., Piou, C., Railsback, S. F., Robbins, A. M., … DeAngelis, D. L. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological Modelling*, *198*(1), 115–126. https://doi.org/10.1016/j.ecolmodel.2006.04.023

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., Thulke, H.-H., Weiner, J., Wiegand, T., & DeAngelis, D. L. (2005). Pattern-Oriented Modeling of Agent-Based Complex Systems: Lessons from Ecology. *Science*, *310*(5750), 987–991. https://doi.org/10.1126/science.1116681

Hall, P. (1988). The city of theory. *The City Reader*, 391–393.

Harley, J. B. (1989). Deconstructing the map. *Cartographica: The International Journal for Geographic Information and Geovisualization*, *26*(2), 1–20. https://doi.org/10.3138/E635-7827-1757-9T53

Harvey, D. (1989). From Managerialism to Entrepreneurialism: The Transformation in Urban Governance in Late Capitalism. *Geografiska Annaler. Series B, Human Geography*, *71*(1), 3–17. JSTOR. https://doi.org/10.2307/490503

Heppenstall, A., Crooks, A., Malleson, N., Manley, E., Ge, J., & Batty, M. (n.d.). Future Developments in Geographical Agent-Based Models: Challenges and Opportunities. *Geographical Analysis*, *n/a*(n/a). https://doi.org/10.1111/gean.12267

Hilber, C. A. L., & Mense, A. (2021). *Why have house prices risen so much more than rents in superstar cities?* Centre for Economic Performance, LSE. https://EconPapers.repec.org/RePEc:cep:cepdps:dp1743

Homer-Dixon, T., Milkoreit, M., Mock, S. J., Schröder, T., & Thagard, P. (2014). The Conceptual Structure of Social Disputes: Cognitive-Affective Maps as a Tool for Conflict Analysis and Resolution. *SAGE Open*, *4*(1), 2158244014526210. https://doi.org/10.1177/2158244014526210

Innes, J., & Booher, D. (2018). *Planning with Complexity: An Introduction to Collaborative Rationality for Public Policy*. Routledge. https://doi.org/10.4324/9781315147949

Innocenti, E., Detotto, C., Idda, C., Parker, D. C., & Prunetti, D. (2020). An iterative process to construct an interdisciplinary ABM using MR POTATOHEAD: An application to Housing Market Models in touristic areas. *Ecological Complexity*, *44*, 100882. https://doi.org/10.1016/j.ecocom.2020.100882

Jokar Arsanjani, J., Helbich, M., & de Noronha Vaz, E. (2013a). Spatiotemporal simulation of urban growth patterns using agent-based modeling: The case of Tehran. *Cities*, *32*, 33–42. https://doi.org/10.1016/j.cities.2013.01.005

Jokar Arsanjani, J., Helbich, M., & de Noronha Vaz, E. (2013b). Spatiotemporal simulation of urban growth patterns using agent-based modeling: The case of Tehran. *Cities*, *32*, 33–42. https://doi.org/10.1016/j.cities.2013.01.005

Jones, G., & Ward, P. M. (2003). *Methodology For Land And Housing Market Analysis*. Routledge.

Kahneman, D., & Tversky, A. (2013). Prospect Theory: An Analysis of Decision Under Risk. In L. C. MacLean & W. T. Ziemba, *World Scientific Handbook in Financial Economics Series* (Vol. 4, pp. 99–127). WORLD SCIENTIFIC. https://doi.org/10.1142/9789814417358_0006

Kitchin, R. (2010). Post-representational cartography. *Lo Squaderno*, *15*, 7–12.

Korzybski, A. (1931). *A NON-ARISTOTELIAN SYSTEM AND ITS NECESSITY FOR RIGOUR IN MATHEMATICS AND PHYSICS*. /paper/A-NON-ARISTOTELIAN-SYSTEM-AND-ITS-NECESSITY-FOR-IN-Korzybski/c29161b8e0971844c0919ea070f6868d28df7adf

Krijnen, M., & Fawaz, M. (2010, July 4). *Exception as the Rule: High-End Developments in Neoliberal Beirut* [Text]. https://doi.org/info:doi/10.2148/benv.36.2.245

Lengnick, M. (2013). Agent-based macroeconomics: A baseline model. *Journal of Economic Behavior & Organization*, *86*, 102–120. https://doi.org/10.1016/j.jebo.2012.12.021

Lin, Z., & Vandell, K. D. (2007). Illiquidity and Pricing Biases in the Real Estate Market. *Real Estate Economics*, *35*(3), 291–330. https://doi.org/10.1111/j.1540-6229.2007.00191.x

Marot, B. (2018). *Developing post-war Beirut (1990-2016): The political economy of "pegged urbanization"* [Phdthesis, McGill University]. https://halshs.archives-ouvertes.fr/tel-03099844

Masad, D., & Kazil, J. (2015). MESA: an agent-based modeling framework. *14th PYTHON in Science Conference*, 53–60.

Mneimneh, S. S., & Fawaz, M. (2019a). *A segment of Beirut's real-estate machine: Housing production and exchange in Tariq el-Jdide (1996-2018)*. https://libcat.aub.edu.lb/record=b2356849

Mneimneh, S. S., & Fawaz, M. (2019b). *A segment of Beirut's real-estate machine: Housing production and exchange in Tariq el-Jdide (1996-2018)*. https://libcat.aub.edu.lb/record=b2356849

Molotch, H. (1993). The Political Economy of Growth Machines. *Journal of Urban Affairs*, *15*(1), 29–53. https://doi.org/10.1111/j.1467-9906.1993.tb00301.x

Morgan, M. S., & Morrison, M. (Eds.). (1999). *Models as mediators: Perspectives on natural and social sciences*. Cambridge University Press.

Morrison, K. (2005). Structuration theory, habitus and complexity theory: Elective affinities or old wine in new bottles? *British Journal of Sociology of Education*, *26*(3), 311–326. https://doi.org/10.1080/01425690500128809

Mosley, T. (2020, January 27). *Vacancy Taxes: The Next Frontier In Housing Policy?* https://www.wbur.org/hereandnow/2020/01/27/vacancy-taxes-housing-policy

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., & Schwarz, N. (2013). Describing human decisions in agent-based models − ODD + D, an extension of the ODD protocol. *Environmental Modelling & Software*, *48*, 37–48. https://doi.org/10.1016/j.envsoft.2013.06.003

Nilsson, H., Rieskamp, J., & Wagenmakers, E.-J. (2011). Hierarchical Bayesian parameter estimation for cumulative prospect theory. *Journal of Mathematical Psychology*, *55*(1), 84–93. https://doi.org/10.1016/j.jmp.2010.08.006

O′Callaghan, C., Feliciantonio, C. D., & Byrne, M. (2018). Governing urban vacancy in post-crash dublin: Contested property and alternative social projects. *Urban Geography*, *39*(6), 868–891. https://doi.org/10.1080/02723638.2017.1405688

O′Sullivan, F. (2020, July 16). Barcelona′s Latest Affordable Housing Tool: Seize Empty Apartments. *Bloomberg.Com*. https://www.bloomberg.com/news/articles/2020-07-16/to-fill-vacant-units-barcelona-seizes-apartments

Pender, K. (2019, January 26). Oakland′s vacant-property tax takes effect, sparking hope—And alarm. *SFChronicle.Com*. https://www.sfchronicle.com/business/networth/article/Oakland-s-vacant-property-tax-takes-effect-13563273.php

Picascia, S., Termos, A., & Yorke-Smith, N. (2018). *Initial Results from an Agent-Based Simulationof Housing in Urban Beirut*. 3.

Prell, C., Hubacek, K., Reed, M., Quinn, C., Jin, N., Holden, J., Burt, T., Kirby, M., & Sendzimir, J. (2007). If you have a hammer everything looks like a nail: Traditional versus participatory model building. *Interdisciplinary Science Reviews*, *32*(3), 263–282. https://doi.org/10.1179/030801807X211720

Roy, A. (2009). The 21st-Century Metropolis: New Geographies of Theory. *Regional Studies*, *43*(6), 819–830. https://doi.org/10.1080/00343400701809665

Sakr, E. (2014, March 17). Real estate demand shifts to suburbs. *The Daily Star*. https://www.dailystar.com.lb/Business/Lebanon/2014/Mar-17/250434-real-estate-demand-shifts-to-suburbs.ashx

Skaburskis, A. (2008). The Origin of "Wicked Problems." *Planning Theory & Practice*, *9*(2), 277–280. https://doi.org/10.1080/14649350802041654

Smaldino, P. E., Calanchini, J., & Pickett, C. L. (2015). Theory development with agent-based models. *Organizational Psychology Review*, *5*(4), 300–317. https://doi.org/10.1177/2041386614546944

Sprague, R. H. (1980). A Framework for the Development of Decision Support Systems. *MIS Quarterly*, *4*(4), 1.

Starfield, A. M., Smith, K. A., & Bleloch, A. L. (1994). *How to Model It: Problem Solving for the Computer Age* (3/16/94 edition). Burgess Intl Group.

Sterman, J. D. (1994a). Learning in and about complex systems. *System Dynamics Review*, *10*(2–3), 291–330. https://doi.org/10.1002/sdr.4260100214

Sterman, J. D. (1994b). Learning in and about complex systems. *System Dynamics Review*, *10*(2–3), 291–330. https://doi.org/10.1002/sdr.4260100214

Tadayon, A. (2019, November 11). Most Oakland vacant parcel owners get a tax break. *The Mercury News*. https://www.mercurynews.com/most-oakland-vacant-parcel-owners-get-a-tax-break

Tesdell, O., Othman, Y., Dowani, Y., Khraishi, S., Deeik, M., Muaddi, F., Schlautman, B., Krug, A. S., & Van Tassel, D. (2020). Envisioning perennial agroecosystems in Palestine. *Journal of Arid Environments*, *175*, 104085. https://doi.org/10.1016/j.jaridenv.2019.104085

van Bruggen, A., Nikolic, I., & Kwakkel, J. (2019). Modeling with Stakeholders for Transformative Change. *Sustainability*, *11*(3), 825. https://doi.org/10.3390/su11030825

Victor, B. (2011). Up And Down The Abstraction Ladder: A Systematic Approach to Interactive Visualization. *WorryDream*. http://worrydream.com/LadderOfAbstraction

Wetzstein, S. (2017). The global urban housing affordability crisis. *Urban Studies*, *54*(14), 3159–3177. https://doi.org/10.1177/0042098017711649

Zaatari, A. (2019). *Housing Production in uneven urban quarters, two case studies from Beirut (Lebanon): Aicha Bakkar and Tallet El Khayyat*. American University of Beirut.

Zhuge, C., & Shao, C. (2018). Agent-based modelling of purchasing, renting and investing behaviour in dynamic housing markets. *Journal of Computational Science*, *27*, 130–146. https://doi.org/10.1016/j.jocs.2018.05.007