EXPLORING URBAN SHRINKAGE BY SIMULATION OF THE HOUSING MARKET IN DETROIT: AN AGENT-BASED MODELING IMPLEMENTATION

This document provide details utilizing the Overview, Design concepts and Details (ODD) Protocol by Grimm et al. (2006) for a model exploring urban shrinkage by simulating a stylized housing market based on Detroit, Michigan. In Section 1 we provide a brief overview of the study area and the agents in the model. Section 2 discuses model design concepts and Section 3 provides implementation details of the model. The model itself was created utilizing NetLogo 6.1 and the model graphical user interface is displayed in Figure 1.

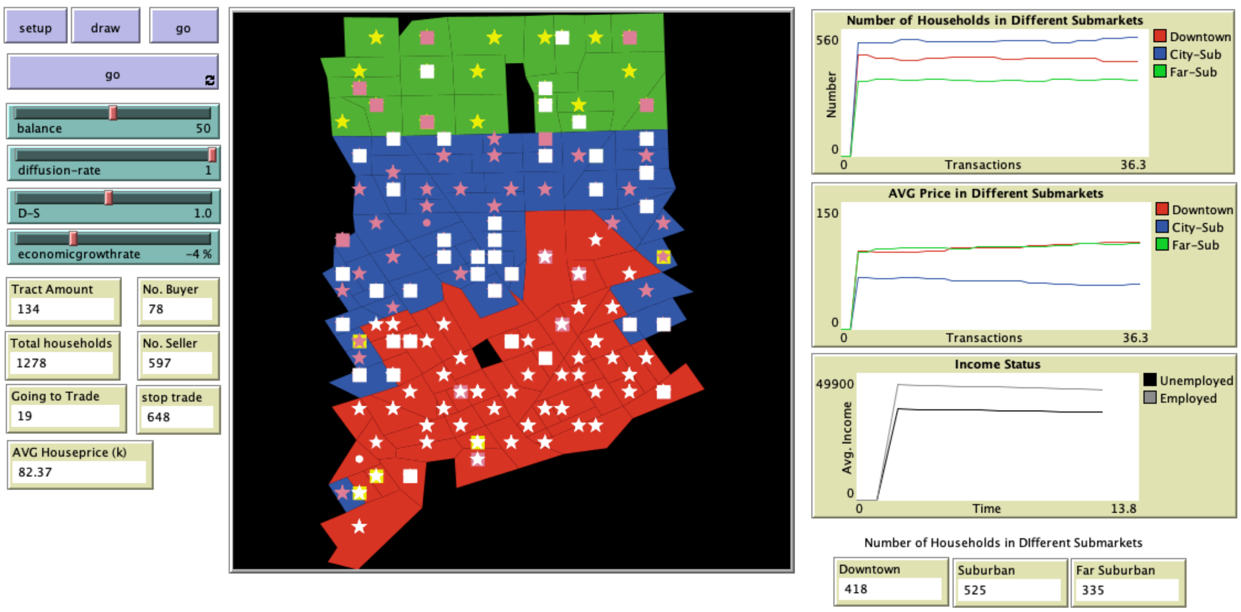

Figure 1: Model graphical user interface, including input parameters, monitors and charts recording key model properties and the study area itself.

1 OVERVIEW

1.1 Study Area and Purpose

The city of Detroit is the largest city in Michigan, located in the Great Lakes area of the United States, which has also been given the moniker the "Rust Belt region." There are many of stories which discuss the greatness of this city during the 1950s – were the automobile manufacturing sector rapidly expanded and its population reached peak (McDonald, 2014). However, the stories today often describe how over the last 60 years the city of Detroit has declined and shrunk and how a city growth can rapidly change into decline if it is focused on only one branch of economic production. One of the most significant phenomenon that this city has witnessed is population loss, a decrease of over 60% in the last 60 years and 25% in the 10 years up to the last census of 2010 (Neill, 2015). With the increasing competition in the automobile manufacturing industry, deindustrialization swept through the city of Detroit and its sounding regions (Rappaport, 2003). Large amounts of vacant properties and vacant land are now distributed to almost every corner of the city. There were approximately 60,000 vacant parcels of land and about 78,000 vacant structures, of which 38,000 were considered to be dangerous in 2014 (McDonald, 2014). This population decline resulted in the housing market shrinking from both the demand and supply sides (Poethig et al., 2017). In addition, the city of Detroit declared bankruptcy on July 18, 2013. Therefore, the city of Detroit is an excellent example of the shrinking city. In the sense it is suffering population loss, deindustrialization, housing market contraction which resulted in city bankruptcy. These economic and population phenomena make Detroit an excellent example of a shrinking city. In the sense it is suffering population loss, deindustrialization, housing market contraction and city bankruptcy. In this work, an agent-based model (ABM) is built to simulate the housing market in the Detroit Tri-county area as displayed in Figure 2 to explore how the housing market reflects urban shrinkage.

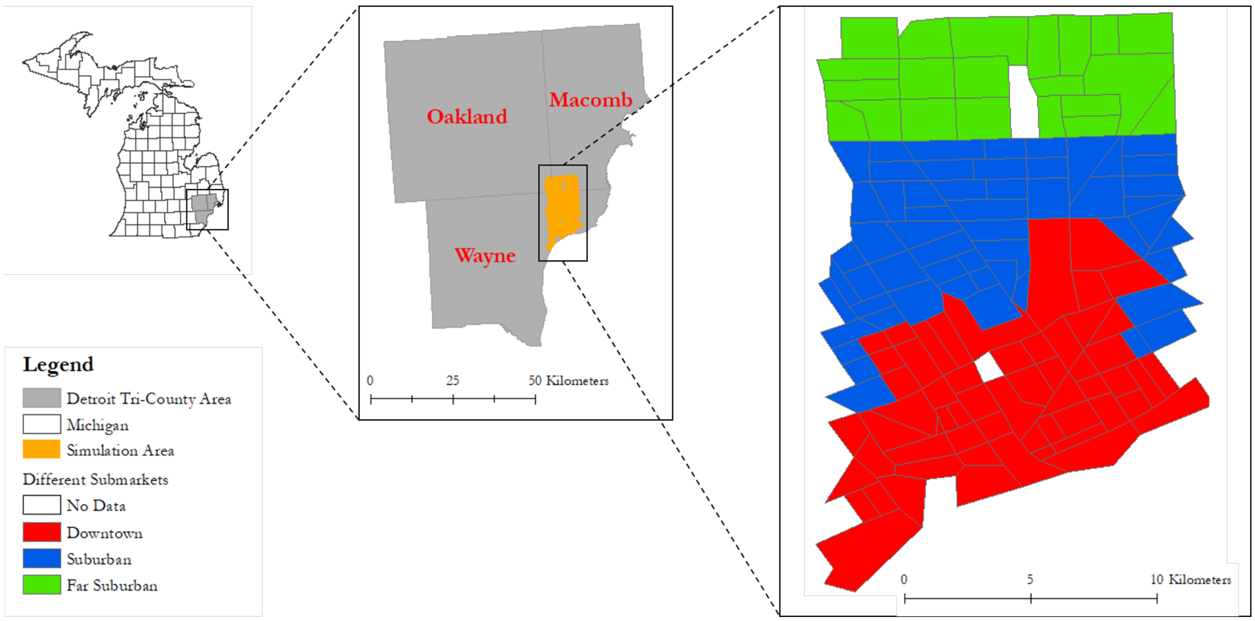

Figure 2: Detroit Tri-County area (middle) and simulation area (right).

1.2 State Variables and Scales

This model focuses on housing trades or transactions within various housing markets, rather than the economy as a whole (however, variables within the model capture employment, as will be discussed next). Hence, trades between buyers and sellers within these different sub-housing markets is simulated by this model. The whole Detroit Tri-County area can be divided in to three sub-housing markets including downtown, city suburban and far suburban housing markets by referencing the spatial data as depicted in Figure 2. Both the downtown area and suburban areas are within Wayne county, the difference is that the downtown area is defined by Detroit opportunity zone data (City of Detroit Open Data Partal, 2019). While the suburban area excludes the downtown area. The rest of the study area we call far suburban, which is not part of Wayne county and is comprised of Oakland and Macomb counites and its distance to downtown area is much further. In order to model, simulate and experiment with the housing market, we chose NetLogo, as it has capabilities to handle the spatial data needed to build the model and allows for rapid prototyping. However, there are constraints to the platform specifically relating to scalability (both in terms of agents and spatial resolution. Hence, instead of modeling the whole study area, only a certain area was selected to build the model, which covers all three submarkets, also shown by Figure 2. The sequence of all function events in this model is displayed by the UML diagram in Figure 3, which demonstrates the model flow and dynamics.

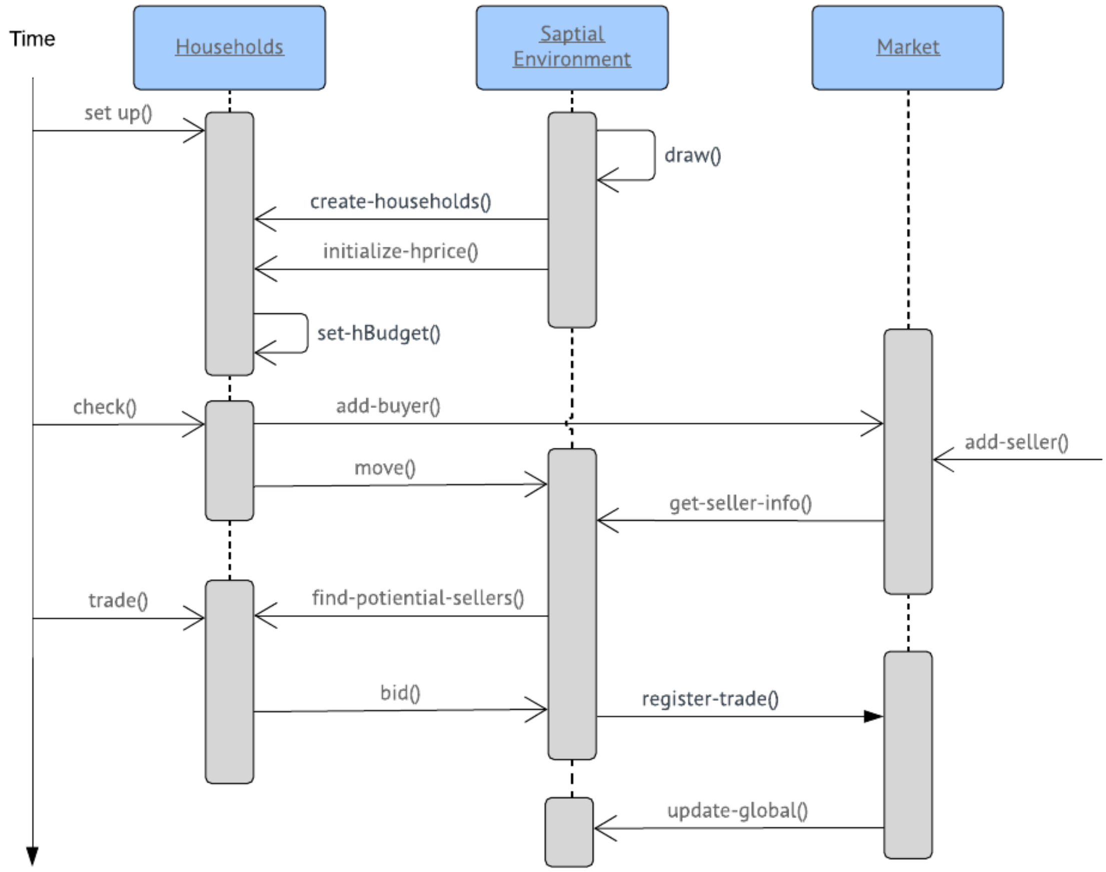

Figure 3: UML of the agent-based model showing the time sequences of the main model functions.

The main agent in this model are households who live in Detroit the Tri-County area. In the model for the purpose of simplification 1 agent is used to represent 100 households. Agents comprise of various attributes that results in a heterogenous population. Except for the attribute HPOLY, the rest of the agents' attributes were selected for inclusion within the model based on relevant literature, which are summarized by Table 1. Agents are heterogenous and vary in their characteristics (e.g. ID, neighborhood type) and finical backgrounds (e.g. income). Furthermore, agents can be categorized into two types: buyer and seller households, and they are all goal-oriented. Buyers have one goal which is finding an affordable house by proposing a bid price to sellers. On the other hand, a sellers goal is to post an asking price and maximize the profits from the trades (this will be further discussed in Section 3.3).

The other component of this model is the environment, which contains three different elements: 1) Geo-spatial; 2) Artificial housing market comprising three different submarkets: Downtown, Suburban and Far Suburban; 3) Economic environment. The geo-spatial environment provides geographic boundary of the whole simulation area and the boundaries of the three sub-housing markets. Also, geo-spatial environment provides a physical environment for all agents moving around. However, artificial housing market is a hidden environment that can capture the trades between buyer households and seller households. As for the economic environment, this is a hidden environment that reflects the economic status of the Detroit area.

The temporal scale in this model is one year that is reflected by the one tick in the NetLogo. Every year, households make decisions to become buyers and trade with sellers.

Table 1: Household agent attributes

Attribute	Description	Reference
ID	Unique ID for households	Filatova et al. (2009)
HNT	Household neighborhood type that indicated which sub-housing market is household located	Detroit Open Data Portal (2018)
HPOLY	Polygon ID indicated which polygon is household on	Authors estimation
HINCOME	Income of the household	Patel et al. (2012), Torrens & Nara, 2007)
HBUDGET	Budget for annual housing cost and purchasing new house	Filatova et al., 2009
BUYER?	Boolean value, if true, buyer household	Filatova et al., 2009
BIDPRICE	Only associate with buyer households	Filatova et al., 2009
SELLER?	Boolean value, if true, seller household	Filatova et al., 2009
ASKPRICE	Only associate with seller households	Filatova et al., 2009
EMPLOYED?	Boolean value, if true, household has job, else, no jobs	Patel et al., 2012
TRADE?	Boolean value, if true, indicates household will trade	Filatova et al., 2009

1.3 Process Overview and Scheduling

As discussed above, household agents are the main components in the model and the key attribute of the household is their incomes (HINCOME), which provides the heterogeneity within the world and is updated as the simulation processes, which is described in 3.3.1. There are several models that have used income to control residential decision making (e.g. Alonso, 1964; Patel et al., 2012). Accordingly, in this model, each household will make decisions based on their income (HINCOME) status, which is either stay or leave the current location. During each time step of the simulation, households will check if they can still afford their current living location based on their annual budgets (HBUDGET) calculated from their income, also this income attribute informs the house trading process. The affordability check will be explained in detail in Section 3.3.1. Once the buyer households decide to enter the housing market, and before the buyer start interacting with sellers, they can choose to enter one of the three submarkets by comparing their annual budget (i.e. HBUDGET) with each submarket's average house price (which will be discussed further in Section 2.2 and 3.3.1). When the buyers enter a certain submarket, they are able to choose sellers within the submarket and bid price with them. The households' decision-making process is displayed by Figure 4.

2 DESIGN CONCEPTS

2.1 Observing

In order to capture the housing market's dynamic, we measure various variables hierarchically. At the macro-level, the overall average house price as well as the total number of buyers and sellers within the study area is recorded at each time step of the simulation. On the meso-level, each different submarket will capture the average prices and household amounts through the entire simulation to reflect the differences among three submarkets.

2.2 Sensing

All household agents know which submarkets they are located in and the prices of the house they currently live in. As will be discussed in Section 3.1.2, they set budgets based on their own incomes. Housing trades is the main interaction in our model. Households who become buyers will use their budget to set the bid-prices (BIDPRICE). Sellers will set the ask prices (ASKPRICE) based on current house prices. Before buyers make trades with sellers, they will know the average ask price of certain area of the submarket, which are interactions with environments as well as indicate buyers' finance capabilities to trade in this area. Once the buyer finds a seller to trade with, they agree upon the price, then trade will happen. Further discussions related to the negotiation process is provided in Section 3.3.1.

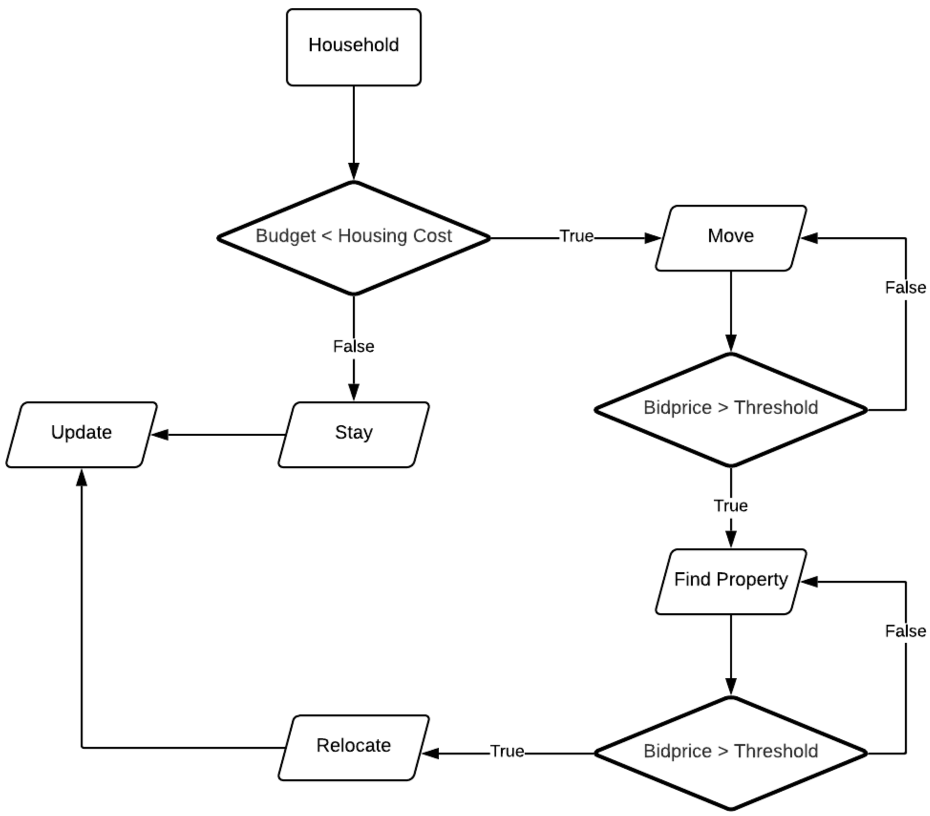

Figure 4: Household decision making process.

3 DETAILS

3.1 Initialization

The initialization of the model is based on socioeconomic and geo-spatial data of the study area. The socioeconomic data (e.g. income, employment status, house prices) comes from the American Community Survey (2010), for each census tract in the study area. This data is used to initialize the number of agents within the simulation. Due to computational constraints we only represent 1% (i.e. 1278) of the total number of households within the study area. As the socioeconomic data is aggregated, we only have average house prices along with upper and lower quartiles within each census tract, therefore in order to assign houses prices we use this distribution (referred to Balance in the model code). Specifically, the total amount of agents is divided by the balance, an equal number of agents are then assigned a house price by adding a random number within the upper quartile range to the average, while the other half are assigned a house price by a random number between lower quantile and the average. For example if the average house price was 50, and the upper and the lower quartiles were 75 and 25 respectively, and we had two agents, one agent would be given a value of 50 + a random number between 50 and 75. While another agent would be given 50 – a random number between 25 and 50. We do this to ensure we get a range of house prices within a census tract. Another input parameter is the diffusion rate which controls the probably of an agent to move out of a submarket (the default setting being 1, that is household agents have the ability to move out of their current sub market if they desire to). This diffusion rate was inspired by Patel et al. (2012) who used the same concept to explore residenytal movment but alos is akin to what we observe with urban growth, whereby redisnets in inner cities move to more subaruabn locations. There are also two other user settable input partamters, one is the ecopnmic growth rate (which is dissced in Section 3.3.2) and the demand and supply conditions (D-S parameter) which bassically controlls the ratio of buyers and sellers.

Table 2: Initialization parameters default values.

Parameters	**Description**	**Default Value**	**Reference**
Diffusion Rate (D)	Control the household movement to another neighborhood	1	(Patel et al., 2012)
Balance	Control the initialization house price of households	50	Author estimation
D-S	Demand and supply, can be controlled by users	1.0	Author estimation
Amount	Initial number agents	1278	American Community Survey (2010)

3.2 Input

Data plays an important role in model parameterization, initialization, verification and validation. Two categories of vector data are applied in this work: spatial data and socioeconomic data. Spatial data include: 1) Detroit city boundary (shown in Figure 2); 2) Tri-county area boundary including Wayne County, Oakland County and Macomb County; 3) All census tract boundaries for the Tri-County area. The census tract boundaries can be associated with socioeconomic data, which can be considered as the linkage between the spatial data and socioeconomic data, which is acquired from American Community Survey (ACS) 2010, as shown by Table 3.

Table 3: ACS Variables for Model Initialization

Variable	**Description**	**Usage**
HU_Count	Total Number of Households	Initialize certain number of agents
HU_I	The number households fall in various income ranging from 50k to 150K	Initialize the agents' income
HU_V_K	The median value of the house value	Initialize the agent house price
HU_VQ_K	Quantile value of the house value	Add variances to the house price
H_EM_R	Employment status	Add employment status for each agent

3.3 Sub Models

3.3.1 Housing Market

Within the housing market, housing trades between buyers and sellers are the key interactions in this model. With respect to modeling markets, Gode and Sunder (1993) were one of the first to demonstrate how agent-based models could be utilized to capture supply and demand. In their abstract model, traders were selected at random to buy and sell goods and through these interactions demonstrated how supply and demand curves observed in "real" world situations could emerge through simulation. Turning to land markets, Filatova et al. (2009) demonstrated how heterogenous agent's with different ask and bid pricing behaviors could generate a land market in a stylized environment while at the same time capturing urban growth which was validated against Alonso's (1964) theory of land rent within a monocentric city. Other researchers have also explored land markets emerging from the bottom up and how they impact land use within cities (e.g. Magliocca, et al., 2011; Torrens & Nara, 2007). For example, Torrens and Nara (2007) simulated the demand and supply sides of a land market to explore urban gentrification in an area of Salt Lake City in Utah. However, while agent-based modeling of residential housing choices and land market have started to show its potential as a valuable methodology to explore urban issues from the bottom up, no studies have explored land markets and urban shrinkage. To our knowledge the only agent-based model to explore urban shrinkage is that by Haase et al. (2010), however, within their model the focus was on residential dynamics and not on housing market dynamics (e.g. buying and selling properties). We would argue that capturing housing markets is essential for understanding urban shrinkage, as the contraction of housing markets is caused by population loss under a urban shrinking situation (Martinez-Fernandez et al., 2012). Hence, a model of urban shrinkage should reflect capture not only residential dynamics but also the trades (or lack of) within the housing market. Therefore, an agent-based model stylized on spatially explicit data is built to simulate the urban shrinkage in the Detroit Tri-county area in order to explore how micro-level housing trades impact on macro-level shrinkage by capturing trades between sellers and buyer within different dynamic sub-housing markets. In this model, household agents decide to trade their houses with each other based on their own income backgrounds, in other words, agent make decisions by their own knowledge. Although, the decision-making is always a complex procedure (Kennedy, 2012), within the model a relative simple process is implemented.

There are total four stages for the simulation process: 1) check current affordability; 2) generate sellers based on demand and supply (D-S) which is defined in Table 2; 3) Search; 4) Trade and move. First, households will check their affordability on their current living sites by comparing their annual budget (HBUDGET) and the minimum housing cost (which we describe below). To check this, all households will set their budgets, which represents 34% of their income (HINCOME) and can be used on annual house fees including property tax, annual maintenance and etc. (Bourne, 2018). The minimum housing cost includes property tax, the house's maintenance fee and mortgage payment. To calculate the minimum housing cost, three percentage numbers are referenced including 1.52% of house price for the property tax, 1.3% of the house price for the annual maintenance fee and 4.54 % of house price for mortgage payment (Brinkley-Badgett, 2017; Pant, 2019; ValuePenguin, 2019). Hence, we set 7.38 % of the house price as the minimum cost which indicates the lowest annual cost for a house. If one household's minimum housing cost exceeds the annual budget (HBUDGET), which indicates this household cannot afford the current house, they will enter the housing market and became a buyer (BUYER?).

Secondly, sellers (SELLER?) will be generated based on the demand and supply status to the other side of the housing trade. The demand and supply status is controlled by the parameter D-S that can be set by users: 1) if D-S is set to 1, it indicates there is equal demand and supply (i.e. there are the same number of sellers and buyers in the model; 2) if D-S is less than 1, demand exceeds supply and less sellers will be generated; 3) if D-S is greater than 1, supply exceeds demand and more sellers will be generated. The third stage is to let the buyers move around the environment.

Thirdly, the parameter diffusion rate (D) is introduced to this model to control the households' movements (akin to searching) to different submarkets, this is a similar concept that Patel et al. (2012) used to control agents choice to leave or stay in slum area. The parameter D value can be also set by users: 1) 0 indicates that buyer households can only move within the same submarket that they are living now; 2) 1 indicates buyer households can move among different submarkets.

As for the key interaction within the model, the trade (and subsequent moving) process comprises of two stages: 1) Find sellers; 2) Bid prices. For the first stage of trade, buyers will find certain sub-market to enter and find seller inside the sub-market to bid price on the houses. For buyers, the main goal is to find affordable houses, so they will check if they can afford houses after the movement to new submarkets. To determine whether they can afford houses or not, buyers have knowledge related to the average house prices of the markets they just moved to, which is calculated by the ask prices (ASKPRICE) of all sellers within the same polygon (HPOLY). The buyers will set the bid price (BIDPRICE), which is 2.5 times of their gross income (CNNMoney, 2015). If their bid price is greater than the average house price of certain submarket, they will enter that submarket and search for affordable houses. If not, they will continually move (i.e. search) until they find affordable submarkets where they can purchase a house. After buyers' movements, the sellers will set the ask price based on the house price and find buyer to complete the trade. Sellers have goal to maximize the profits from the trade, so they will choose the buyer with the best bid price. After the trade is completed, the trade will be registered by the housing market.

3.3.2 Economic Environment

The economic environment is the invisible hand in this model, which impacts the income (HINCOME)of each household and the house prices (Patel et al., 2012). As shown equation 1, the incomes' dynamics are based on economic growth and employment status of the agents. I_{t+1} is the income at time $t+1$, It is the income at time t and G is the economic growth. The α represents the employment status. If one household has job, α will be the *ln* of G's absolute value, if not, will be -0.1.

$$I_{t+1} = I_t(G + 1) + \alpha * I_t \tag{1}$$

During the simulation, the house prices will also have dynamic changes affected by the economic growth (G) rate. However, the G will impact the price based on different submarkets. The house price is updated by Equation 2, where H_{t+1} represents house price at time t +1 after updating, H_t reflects the original house price at time t, G is the economic growth.

$$H_{t+1} = \begin{cases} H_t\,(1 - 0.5\,G) & \textit{Downtown} \\ H_t\,(1 + 0.75\,G) & \textit{City Suburban} \\ H_t\,(1 - 0.25\,G) & \textit{Far Suburban} \end{cases} \tag{2}$$

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