1 Supplementary Material: ABM Description

We describe the ABM in terms of structure and agents' behaviours in this section. The NetLogo source code for the ABM is also available in a GitHub repository upon request from the first author.

1.1. Parameters: Agents and Pixels

On the one hand, the agents' parameters are grouped into five categories: (1) market preferences; (2) land preferences; (3) budget constraints; (4) demography; and (5) relocation parameters. On the other hand, Pixels have four parameter categories: (1) land use; (2) location; (3) land plot attributes; and (4) markets. For conciseness, Table S1 lists the agents and pixels parameters.

Table S1, Agents and Pixels Parameters

	Parameter Name	Value	Units	Type
Agents	Exploration Trials	[1, UC]	Trial	Integer
	Relocation Trials	[1, UC]	Trial	Integer
	Age	UC	Year	Integer
	Breeding Age	UC	Year	Integer List
	Relocation Age (s)	UC	Year	Integer List
	Death Age	UC	Year	Integer
	Integrated Motivation Per Market	[0, 4]	N/A	Float
	Identified Motivation Per Market	[0, 4]	N/A	Float
	Introjected Motivation Per Market	[0, 4]	N/A	Float
	External Motivation Per Market	[0, 4]	N/A	Float
	Area Weight	[0, 1]	N/A	Float
	Number of Street Exposure Weight	[0, 1]	N/A	Float
	Proximity to Service Weight	[0, 1]	N/A	Float
	Budget	[0, 1]	N/A	Float
	% Spent on Non-Housing Commodities	[0, 100]	N/A	Float

Pixels	Land Use Type	N/A	N/A	Character
	Location	Min(x-cor) – Max(x-cor)	Pixel	Integer
		Min(y-cor) – Max(y-cor)	Pixel	Integer
	Area	UC	m^2	Float
	Number of Street Exposure	[1, 4]	Street	Integer
	Market Type	N/A	N/A	Character
	Unit Price	[0, UC]	Price / m^2	Float

UC stands for UnConstrained, N/A stands for not applicable, cor stands for coordinate

1.2. Agents Behaviour: Utility and Budgets

During relocation, agents calculate both the output and procedural utility for the pixels under consideration. Subsequently, agents calculate an overall utility to assess and compare the different pixels (see equation 1).

$$U_{i,b|j} = OU_{i,b} + PU_{i,b|j} \tag{1}$$

Where, for a buyer *b* buying a land plot *i* given a process *j*, $U_{i,b|j}$ is the overall utility, $OU_{i,b}$ is the output utility and $PU_{i,b|j}$ is the procedural utility.

Output utility depends on the utility per land plot attributes and the agents' preference weights. The ABM uses a linear utility formula (Acevedo et al., 2008; Magliocca & Walls, 2018; Satake et al., 2007 e.g.) to calculate output utility (see equation 2). It also uses a linear normalization for the utility per attribute (see equation 3).To account for the law of diminishing marginal utility, the ABM uses an observed diminishing utility factor instead of assuming a logarithmic formula.

$$OU_{i,b} = \sum_{a=1}^{n}(u_{i,a} * \gamma_{b,a}) \tag{2}$$

$$u_{i,a} = \begin{cases} \left(\frac{z_{i,a}}{\max(z_a)}\right) * \sigma_{b|a}, & if\ benifit\ increases\ with\ attribute's\ increase \\ \left(1 - \frac{z_{i,a}}{\max(z_a)}\right) * \sigma_{b|a}, & otherwise \end{cases} \tag{3}$$

Where $u_{i,a}$ is the utility of a land plot i due to an attribute a, $\gamma_{b,a}$ is the weight attached by a buyer b to a land plot attribute a, $z_{i,a}$ is the value of the attribute a of a land plot i and $\sigma_{b|a}$ is the diminishing utility factor for a buyer b given an attribute a.

For procedural utility, agents calculate the aggregate procedural utility and then transform it to a scale comparable to the output utility. The procedural utility weight factor ($\beta_{i,b|j}$) is introduced to the ABM as an input based on contextual observations. Details on the mathematical formulation of procedural utility is available in the paper.

For budgets, agents calculate their Willingness to Pay (WTP) during the relocation process. WTP depends on the utility gained from the pixel, the agent's budget and the ratio it spends on the non-housing commodities (Filatova et al., 2009, 2011) (see equations 4 and 5).

$$WTP_{i,b|j} = \frac{Y_b * U_{i,b|j}^2}{q_{i',b|j'}^2 + U_{i,b|j}^2} \tag{4}$$

$$q_{i',b|j'} = \frac{(\rho^{2R_b - 1}) * \max(U_{i,b|j})}{2} \tag{5}$$

Where $WTP_{i,b|j}$ is the willingness of a buyer b to pay for a land plot i given a market process j, Y_b is the budget of a buyer b, $U_{i,b|j}$ is the overall utility of a land plot i that a buyer b is considering given a market process j, $q_{i',b|j'}$ is a budget factor of a buyer b given a highest utility land plot i' using a process j', ρ is a constant factor, R_b is the ratio a buyer b spends on non-housing commodities from his whole budget Y, $max(U_{i,b|j})$ is the highest utility gained by a buyer b from any land plot i using a process j.

1.3. Pixels: Price formulation

For prices, pixels first calculate their price per meter squared based on the distance from service attribute. This unit price is then used along with the pixels' area to calculate an overall price (see equation 6). These overall prices are then modified using a variability factor and a markets dynamics factor (see equation 7).

$$P_{i|j} = \frac{Y_s * U_{i,b|j}^2}{q_{i',b|j'}^2 + U_{i,b|j}^2} \tag{6}$$

Where $P_{i|j}$ is the price of a land plot *i* given set by a seller *s* a market process *j*, Y_s is the budget the seller *s* expects for potential buyers, $U_{i,b|j}$ is the overall utility of a land plot *i* that a seller *s* is considering given a market process *j*, $q_{i',s|j'}$ is a budget factor of a seller *s* given a highest utility land plot *i'* using a process *j'*, ρ is a constant factor, R_s is the ratio a seller *s* expects buyers to spend on non-housing commodities from their whole budget Y_s, $max(U_{i,s|j})$ is the highest utility gained by a seller *s* from any land plot *i* using a process *j*.

For clarity, the variability factor accounts for different price ranges in a realistic context. It remains constant for each pixel along the whole simulation. In contrast, the markets dynamics factor changes across the simulation according to the market type. It keeps prices constant for the fixed and random markets, and it allows for price fluctuations in supply-demand markets (see equation 8)

$$\delta_j = \begin{cases} 1 & for\ fixed\ and\ random\ markets \\ \max\left(\frac{D_j}{S_j}, \delta_j'\right) & for\ supply - demand\ market \end{cases} \tag{7}$$

Where D_j is the number of pixels agents demand in a given market *j* over a specific period, S_j is the number of pixels supplied in a given market *j* over a specific period and δ_j' is the highest market dynamics factor of a market process *j*.

In summary, pixels calculate their own prices similar to how buyers set their WTP. The calculated prices slightly differ due to different expected buyers' budgets and price variability factors. During the runs, prices remain constant for the fixed and random markets, whereas they vary in the supply-demand market.

1.4. Events Sequence

The ABM includes two phases: the setup phase (see Figure S3); and the run phase. In the setup phase, the model generates a set of pixels within a space of given dimensions. The pixels are allocated a land use type, a set of attributes and a market type. At that point, the model allocates residential and service pixels and calculates the distances from service for each pixel. The price of each pixel is accordingly allocated finalising an abstract representation of a land use context.

The model then introduces a set of agents with three attributes preferences, four motivational values per market and a set of demographic properties. These agents apply the exploration sub-model – they move to a service pixel to explore a random set of unoccupied pixels within their awareness radius (bounded rationality). Agents calculate the output, procedural and overall utilities for each explored pixel. The mean values of the overall utilities dictate a utility threshold for satisfactory pixels.

Using such threshold, the agents start the relocation sub-model. Similar to the exploratory one, agents randomly search for vacant pixels, but they calculate their WTP for every selected pixel (see equations 4 and 5); agents relocate to the first pixel that is satisfactory (utility > utility threshold) and affordable (WTP > price) – the model is satisficing and not maximizing. If the agent fails to find a satisfactory pixel within its maximum relocation trials, it leaves the system. After all agents undergo the exploration and relocation sub-models, the setup phase ends (see Figure S1).

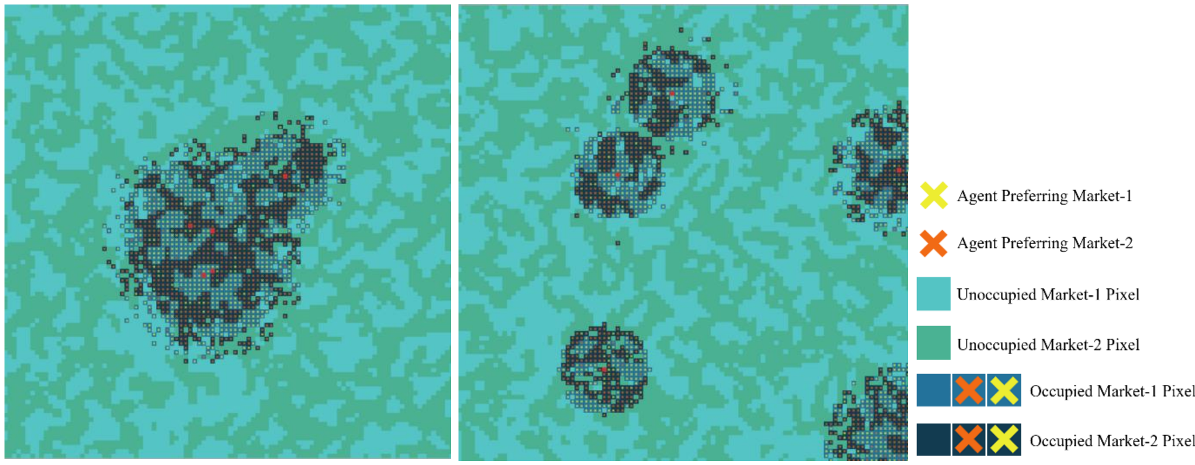

Figure S1, Two Initialization Samples Using 1500 Initial Agents and five service pixels

The run phase is applied over a yearly basis. Every year new immigrants are introduced to the system and all current agents age. On the one hand, the new immigrant agents follow the same setup procedures.

On the other hand, the current agents' ages are compared to their corresponding breeding age(s), relocation age(s) and death age. At breeding age(s), the agents create a similar child agent at an age of zero. This child agent remains attached to its parent agent until it reaches its relocation age. At relocation age(s), the agents undergo the exploration and relocation sub-models. Three differences are present however: (1) the current occupied pixel is included in the mean utility threshold; (2) if an agent finds a satisfactory and affordable pixel, its previous pixel becomes vacant; (3) the final allocated pixel is chosen based on the target pixel's market type. For fixed and supply-demand markets, the agent simply relocates to its chosen pixel. For the random market, the agent is allocated a random pixel within its awareness radius. At the death age, the agents leave the system and their pixels become vacant. The only exception is when an agent dies while still having an attached child. In this case, the child occupies its dead parent's pixel until it reaches its own relocation age.

After all ages are checked and all immigrants are introduced, the model modifies the pixels' prices according to their market type. Fixed and random market prices remain constant across the simulation. However, the supply-demand market prices are modified according to the changes in the number of occupied and unoccupied pixels during this simulation year (see Figure S2). Subsequently, the year terminates and the ABM model proceeds to the next year.

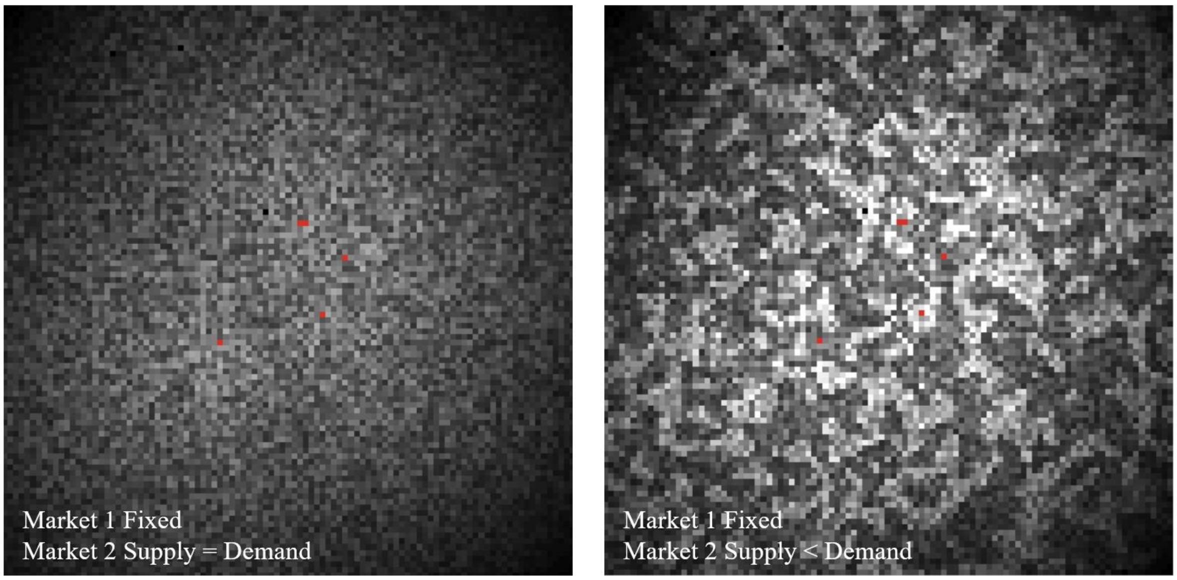

Figure S2, Pixel Price Sample from a Simulation Run Where Darker Colours Indicate Lower Prices

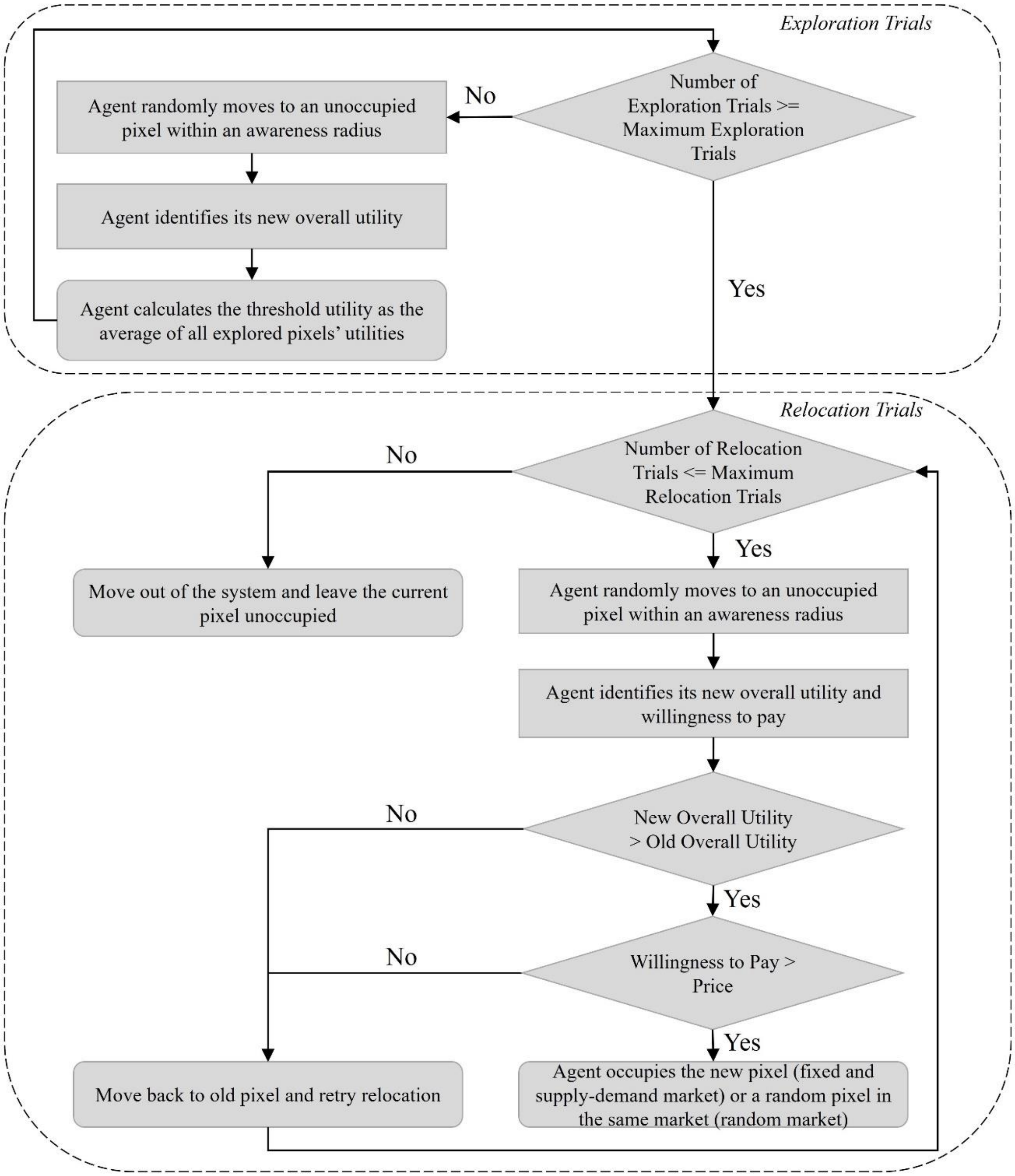

Figure S3, Immigrant Agent and New Agent Initialization Phase Flow Chart

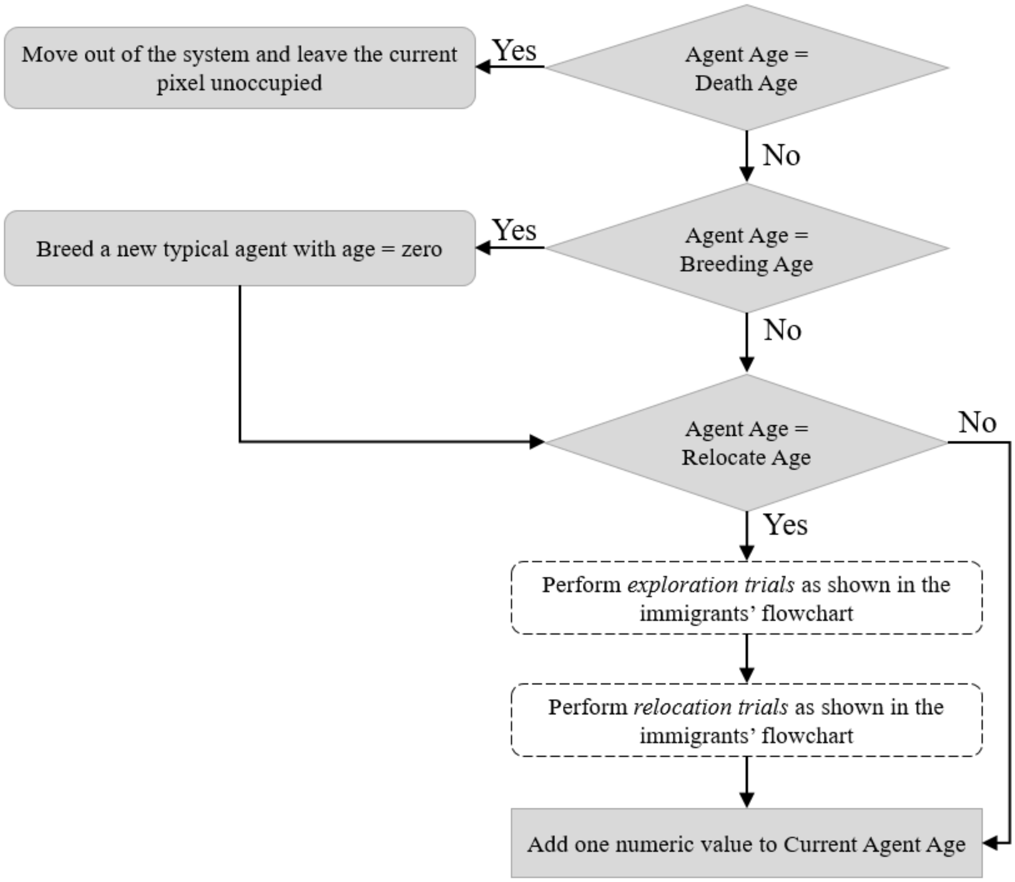

Figure S4, Aging Agents Run Phase Flow Chart

1.5. Market Representation

The ABM is capable of representing markets including budget bound agents with oppressed competitive bidding. That is, buyers acquire a land plot one their willingness to pay is higher than the price (i.e., willingness to accept) the seller sets. According to Huang et al. (2013), this model falls on 'level 1' across a four level categorisation based on market representations. Level 0 (L0) includes agents that are not budget bound. Level 0.5 (L0.5) includes a bidding process but without budget constrains; that is buyers have infinite money and bid based on utility only. Level 1 (L1) includes budget bound buyer but without competitive bidding; sellers make a transaction once they find a buyer with a willingness to pay higher than the set price. Level 2 (L2) includes budget bound buyers that engage in competitive bidding. This is the closest representation to markets that include bidding; however, it is the most complex.

Huang et al. (2013) tested ABMs representing markets at the four levels through an experiment that adjusts agents heterogeneity. Their results show high discrepancies between levels that include budget constraints (L0 and L0.5) and levels that do not (L1 and L2). L1 and L2 showed similar populations, close transaction prices and close budget spatial distribution (Theil index) at the end of the run. This implies that L1 ABMs are sufficient to represent markets, and L2 ABMs is a more accurate representation of reality that leads to minor changes in the outcomes. Deciding to add competitive bidding (L2) or not (L1) requires addressing the aim of the ABM and the study at hand.

The aim of this study is to showcase the effect of procedural utility on the urban context in terms of segregation and satisfaction of agents (see manuscript). Agents in this model have preconceptions towards markets in the form of PU. This is unique to this application unlike ABMs where agents do not have any preconception towards the details of the exchange process they undergo. Abstracting the markets does not affect these preconceptions, and accordingly does not affect their impact on the results. Therefore, it is acceptable to simplify markets by suppressing bidding in this ABM, so long as we simulate more than one market and associate a set of motivations to each. This does not highly affect the results as long as budgets are considered as per Huang et al. (2013).

That is not to say adding further details to the presented ABM market mechanisms does not lead to any benefits. It can improve the predictive capacity of the ABM – in exchange for increased complexity and challenges with interpreting the effect of procedural utility on urban trends. We stress that providing a predictive model is not the aim of this paper. Hence, adding more details to the exchange process in the ABM is beyond the focus of this study. It adds to the model complexity without contributing to the effect of procedural utility on urban trends.[1]

2 Notes on Experiments and Greater Cairo Case Study

We apply the model to the case of Greater Cairo because it is a context with multiple formal informal dynamics. The ABM represents Greater Cairo's context as a set of pixels representing formal and informal settlements. Figure S5 depicts the spatial distribution of formal and informal settlements in Greater Cairo, and it shows its representation in the ABM.

We define three experiments (E1, E2 and E3), and we run each experiment with the procedural utility weight $\beta_{i,b|j}$ set to zero (β_0) and set based on observation in Greater Cairo (β_{GC}). Experiment 1 assumes buyers are not budget bound. Experiment 2 assumes buyers are budget bound and sets prices to fixed values regardless of supply and demand. Experiment 3 allows supply and demand to dictate land prices. We run each experiment for 30 years to explore urban growth and segregation trends. Figure S6 shows sample spatial results for the three experiments. For further details on the experiments, see manuscript.

In this section, we extend the model results to a measure of isolation. We include a set of graphs for the diversity index results (see Figure S8). We then discuss the model validation in section 3.

2.1. Isolation Results

The isolation, in this study is a measure of the spatial distribution of satisfied and dissatisfied buyers, following a logic similar to Schelling's (1971) model. If a buyer is surrounded by

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[1] It should be noted that the authors incorporated a full bid-auction process in the ABM. By comparing different experiments, we observed similar effects for procedural utility on segregation as the ones presented in the manuscript. We concluded that minimising complexity is beneficial given our aim to highlight the effect of procedural utility, rather than develop a predictive model.

more than four buyers with a different land market preference from themself, the buyer is considered isolated.

2.1.1. Effects on Procedural Utility

The level of spatial isolation is substantially lower for A1 buyers at E1-β_0 in comparison to E1-β_{GC} (see Figure S7). The percentage values reach a mean of 4.4 percent for E1-β_0 and 56.2 percent for E1-β_{GC} after 30 years. However, A2 buyers have generally low isolation rates in both sets of $\beta_{i,b|j}$ runs. E1-β_0 still has slightly lower A2 isolation percentages at 6.9 percent in comparison to 11.6 percent at E1-β_{GC}. At E1-β_0, these low isolation values can be explained by the low net number of buyers. This leads to a lower number of neighbours per buyer agent. Hence, a buyer is more likely to have less than four surrounding buyers with opposed market preferences. In such case, the buyer under consideration is counted as non-isolated.

At E1-β_{GC}, the high isolation rate for A1 buyers can be explained through the high net number of buyers and the low number of M1 plots. Similarly, as with satisfaction, this combination leads to shortages in M1 plots which diverts A1 buyers to their less preferred M2 plots. These diverted buyers are very likely to be isolated since M2 plots are generally more occupied by A2 buyers due to their appealing procedural utility. In contrast, the M2 buyers' isolation rate is kept low at E1-β_{GC} due to the abundance of M2 plots and the price barrier for M1 plots. In other words, A2 buyers are initially less likely to seek M1 plots due to their aforementioned shortage. Further, even if A2 buyers do try to relocate to M1 plots, high M1 prices and low A2 buyer budgets lead to high rates of unaffordability.

2.1.2. Procedural Utility and Budgets

The isolation of buyers is analysed for A1 and A2 buyers separately. For A1 buyers, E1-β_{GC} has the highest mean percentage of isolated buyers, 56.3 percent at 30 years. E2-β_{GC} and E3-β_{GC} have mean isolation rates of 19.1 percent and 20.8 percent, respectively. These isolation values align with observed spatial clustering of markets and the simulated satisfaction rates in GC. In E1-β_{GC}, low satisfaction rates are associated with A1 buyers occupying M2 plots due to shortages in M1 plots (see Figure S6 in supplementary material). These A1 buyers have high numbers of A2 neighbours which leads to high isolation rates. However, by considering budgets and higher satisfaction rates, A1 buyers are more likely to buy within their preferred market. This leads to similar neighbours and substantially lower isolation values in E2-β_{GC} and E3-β_{GC}.

For A2 buyers, similar trends are observed, but with lower isolation percentages. E1-β_{GC}, E2-β_{GC} and E3-β_{GC} rank from highest to lowest with minor differences – they have mean isolation values for A2 buyers of 11.6 percent, 8.2 percent and 4.4 percent respectively (see Figure S7). These low values may be because A2 birth rates are higher than A1, which leads to a higher population ratio in comparison to A1 buyers. Subsequently, A2 buyers are more likely to be surrounded by similar buyers leading to lower isolation rates.

3 Validation

The model validation is tied to our aim to understand the effect of procedural utility on the urban context. We do not aim to accurately represent GC and predict its urban future. Hence, it is not relevant to validate the model on the basis of its outputs. Instead, we apply the validation on the basis of the mechanisms of the decision-making process.

The model is based on observed stated preferences in GC. During these observations, individuals are asked to choose between two realistic plots with different attributes in different land markets. The model replicates this decision process by: (1) restricting the agents choices between two land plots following the survey design; and (2) Generating the agents attributes based on the statistical relevance of the survey results. That is, all the attributes are generated over a normal distribution with a mean value from the survey results and a standard deviation of 10 percent. This reflects the 10 percent margin of error in the survey results. On that basis, the ABM is valid for understanding procedural utility as it replicates the behaviours observed in the GC survey.

Although validating the ABM results is not relevant, the model outcomes are close to the historical urban growth in GC. The model runs for 30 years from 1975 to 2005, and experiment 3 is the closet representation of markets in GC. The final population in the year 2005 in experiment 3 reaches approximately 13,000,000 individuals – by assuming every household to include 5 individuals. This is of the same magnitude of an estimated population of 15,000,000 in GC in 2005. The ABM then has a prediction error of 13.33 percent, and this can be improved by increasing the sample size in GC.

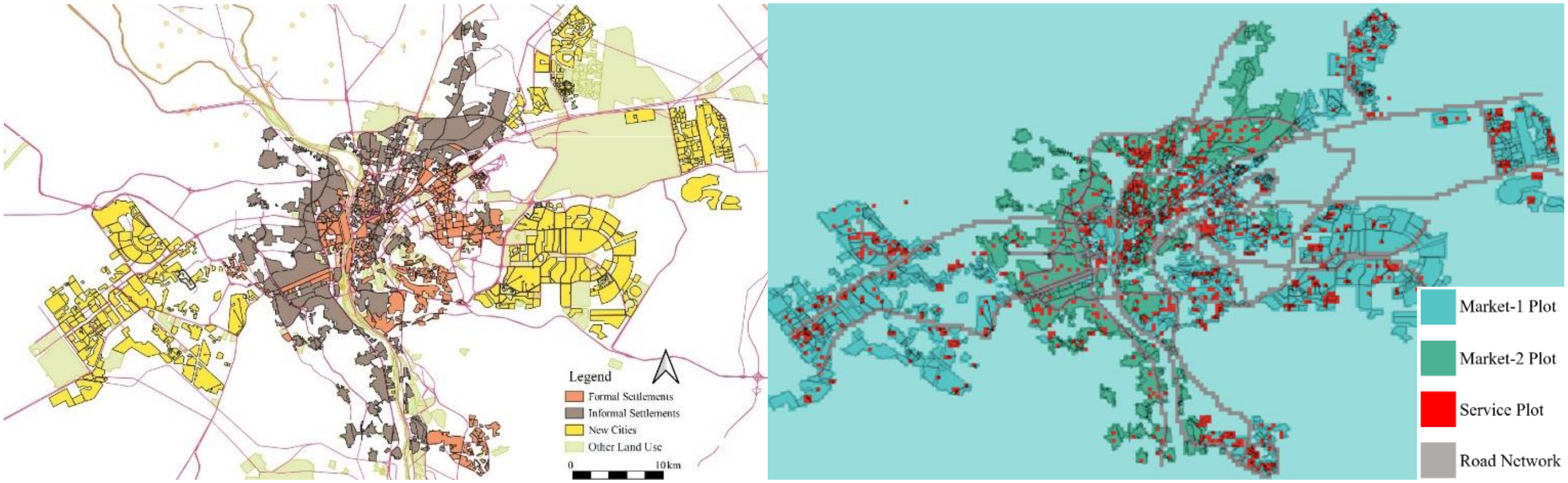


Figure S5, GC map (left) and ABM GC Initialisation State (right)

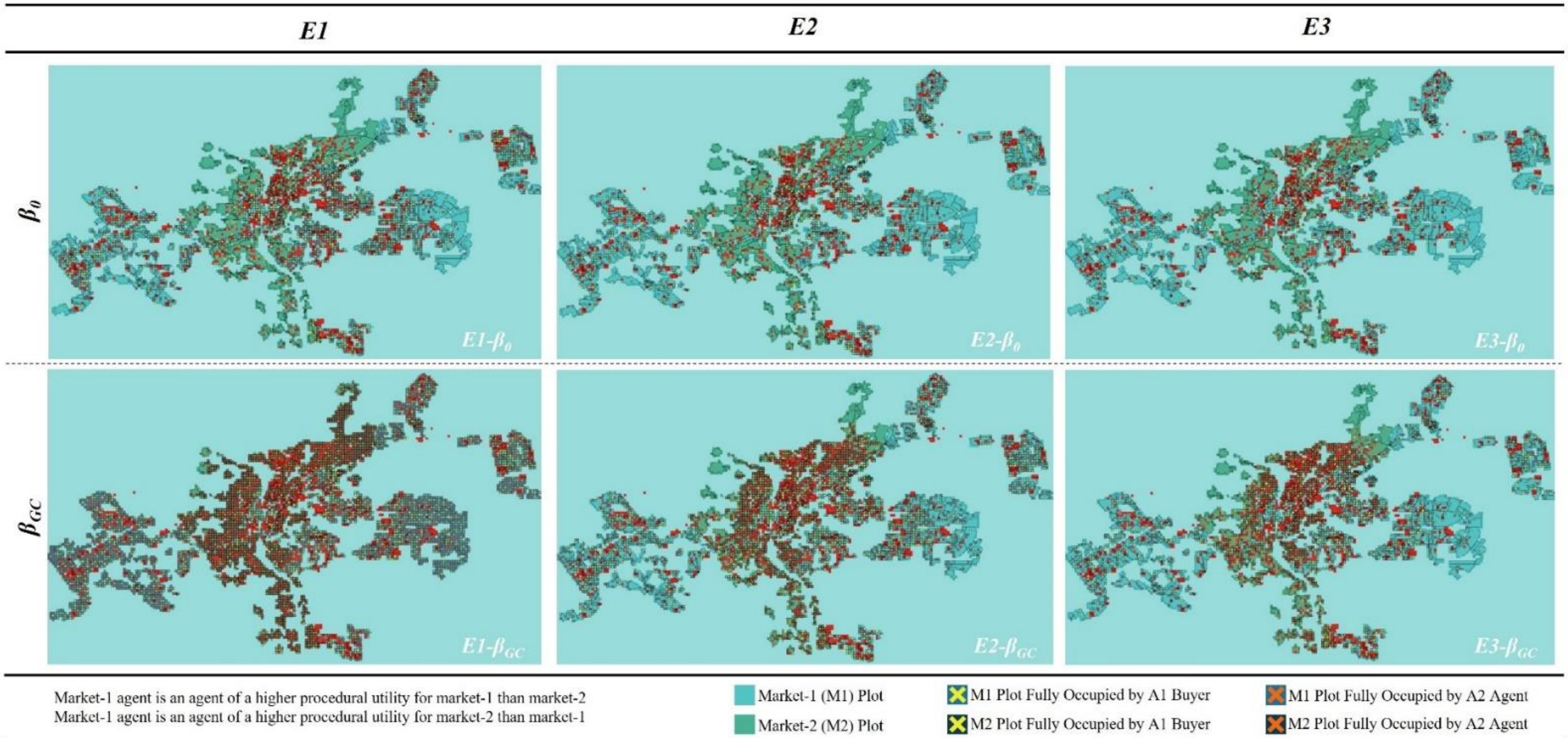
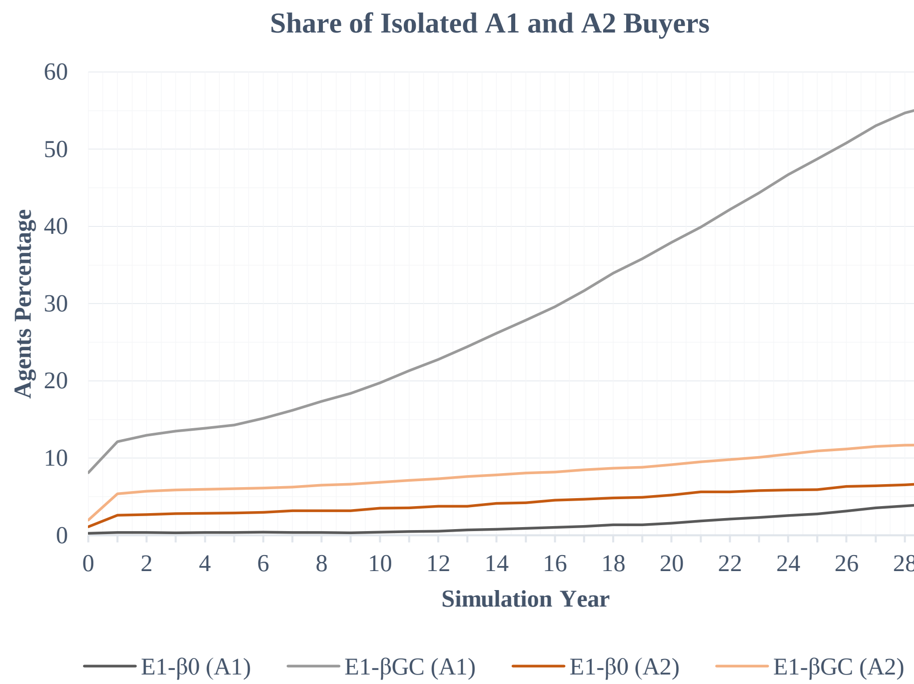


Figure S6, Sample Simulation Results after 30 Year Runs



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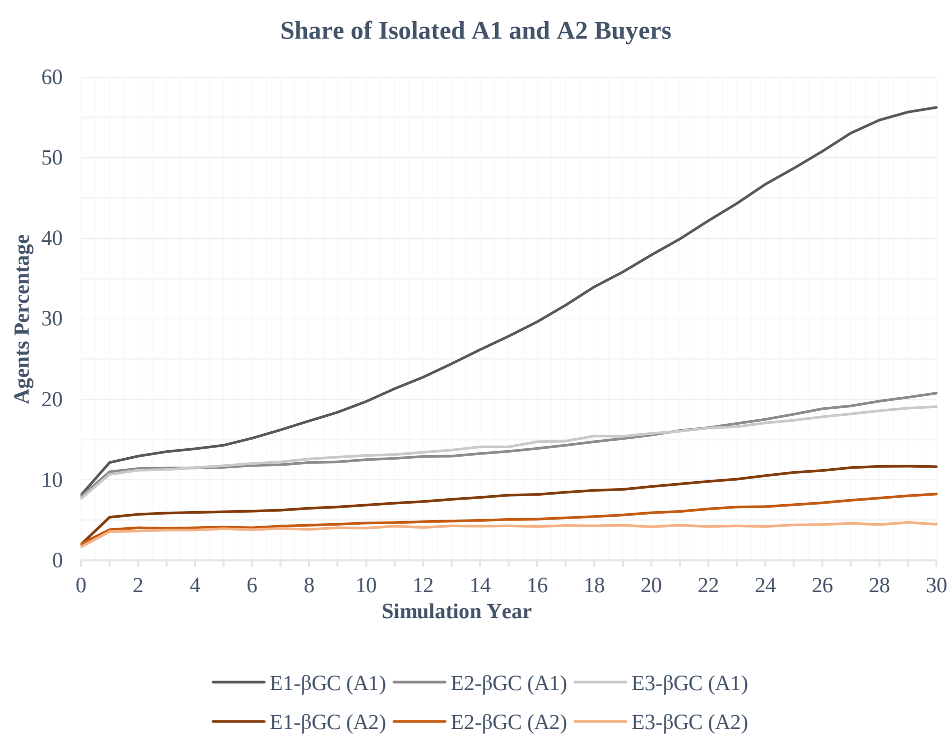

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240 **Figure S7, Isolation Results**

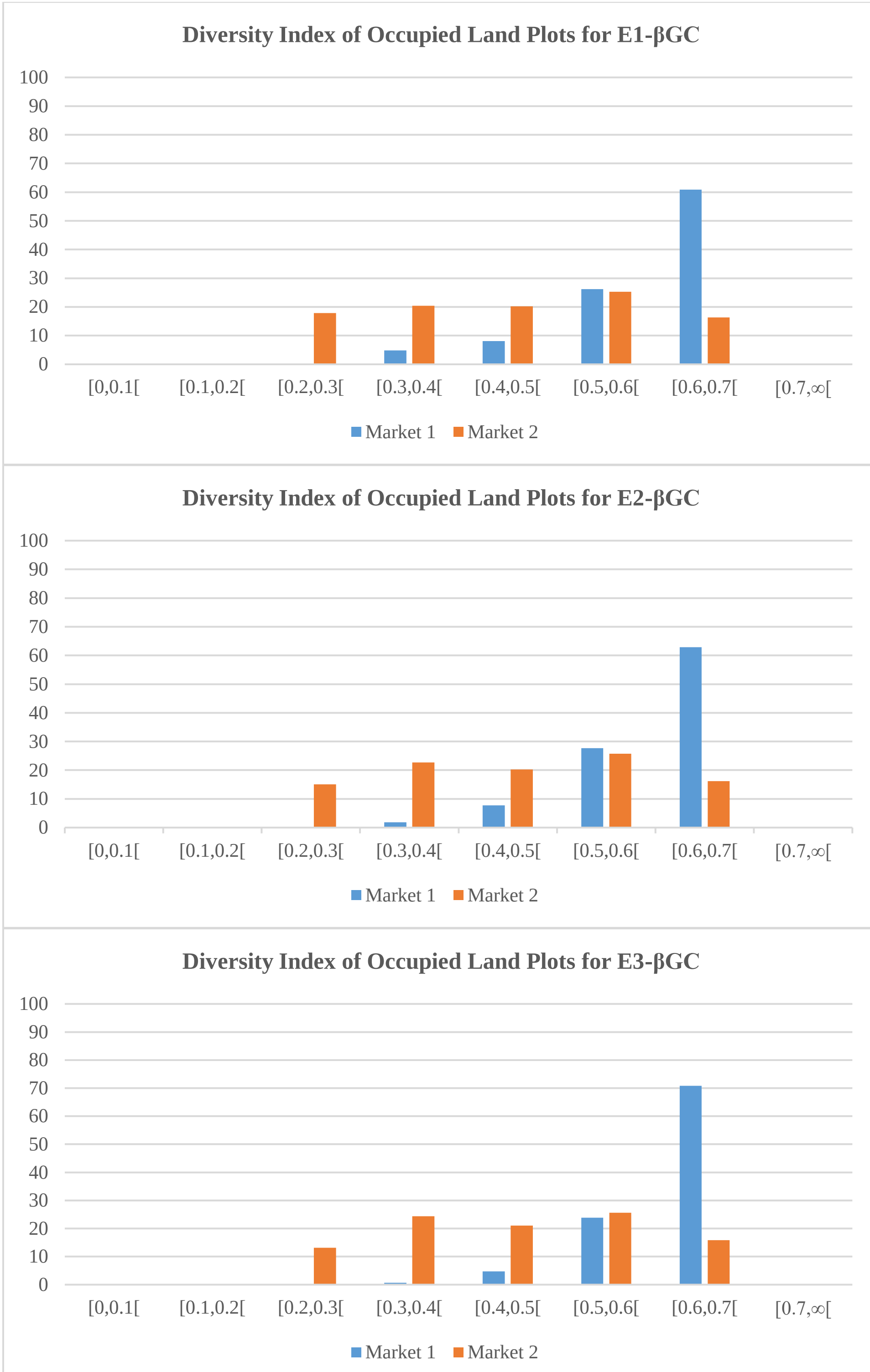

Figure S8, Diversity Index for M1 and M2 Plots at 30 Years

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