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Effects of agent heterogeneity in the presence of a land-market: A systematic test in an agent-based laboratory

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A B S T R A C T

Representing agent heterogeneity is one of the main reasons that agent-based models become increasingly popular in simulating the emergence of land-use, land-cover change and socioeconomic phenomena. However, the relationship between heterogeneous economic agents and the resultant landscape patterns and socioeconomic dynamics has not been systematically explored. In this paper, we present a stylized agent-based land market model, Land Use in eXurban Environments (LUXE), to study the effects of multidimensional agents' heterogeneity on the spatial and socioeconomic patterns of urban land use change under various market representations. We examined two sources of agent heterogeneity: budget heterogeneity, which imposes constraints on the affordability of land, and preference heterogeneity, which determines location choice. The effects of the two dimensions of agents' heterogeneity are systematically explored across different market representations by three experiments. Agents' heterogeneity exhibits a complex interplay with various forms of market institutions as indicated by macro-measures (landscape metrics, segregation index, and socioeconomic metrics). In general, budget heterogeneity has pronounced effect on socioeconomic results, while preference heterogeneity is highly pertinent to spatial outcomes. The relationship between agent heterogeneity and macro-measures becomes more complex when more land market mechanisms are represented. In other words, appropriately simulating agent heterogeneity plays an important role in guaranteeing the fidelity of replicating empirical land use change process.

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1. Introduction

Land-use and land-cover change (LUCC) in the context of an urban environment is the result of the dynamics of coupled human and natural systems. Agent-based models (ABMs) have advantages in simulating the complexity (e.g. nonlinearity, path-dependence, heterogeneity, and emergence) in these systems and integrating empirical findings from multiple disciplines (e.g. geography, sociology, economy, and psychology) (Batty, 2005; Liu et al., 2007). For these reasons, both theoretical and empirical ABMs have been developed to simulate urban LUCC (Clifford, 2008; Grimm, 1999; Liu et al., 2007; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007; Parker, Manson, Janssen, Hoffmann, & Deadman, 2003; Robinson et al., 2007).

One of the essential advantages of ABM is its ability to connect heterogeneous individual decision-making processes with emergent spatial patterns. In fact, empirical studies show that the heterogeneity among agents, including preferences for amenity, risk perceptions, income differences, demographic and household characteristics and different strategies of land development and management, plays a pivotal role in determining spatial landscape patterns and socioeconomic outcomes (Brown & Robinson, 2006; Ghoulmie, Cont, & Nadal, 2005; Ligmann-Zielinska, 2009; Magliocca, Safirova, McConnell, & Walls, 2011). In addition to agent heterogeneity, representations of land-market processes, for example, preferences, budget constraints, and competitive bidding, are important factors in bridging the gap between rigorous spatial dynamics models and existing ABMs that omit these components (Irwin, 2010; Parker et al., 2012).

Although agent heterogeneity and market representation are main components in modeling urban LUCC, the effects of agent heterogeneity under various land market representation have not been systematically inspected (Irwin, 2010; Parker & Filatova, 2008; Parker et al., 2012). The deficiency lies in several aspects.

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First, few models incorporate market process. Second, even though almost every ABM has agent heterogeneity to some extent, few studies have systematically tested the effects of continuous variation in the magnitude of agent heterogeneity on the output, especially in a model that has land market mechanisms (Parker et al., 2012). Moreover, several studies come to conflicting conclusions regarding the effects of agent heterogeneity on projected land-use patterns (more details in Section 2.3). Third, the interactions between multiple sources of agent heterogeneity may be overlooked since some models treat agents with a single heterogeneous characteristic.

Using a stylized Agent-based land market model (ABLMM), named LUXE (Land Use in eXurban Environments), which simulates residential choices under different levels of market representations, we systematically investigate the multidimensional effects of agent heterogeneity on spatial and socioeconomic patterns of LUCC. In our model, there are two sources of agent heterogeneity. One is income heterogeneity, which imposes constraints on the affordability of buying land; the other is preference heterogeneity, which influences locational choice. Landscape measures (e.g. edge density) as well as socioeconomic measures (e.g. evenness index) are used to analyze the spatial patterns of land use and land price. The innovation of this study is to comprehensively explore the effects of agent heterogeneity in an ABLMM. The findings could potentially provide insights on the design of ABMs as well as reconcile some conflicts in the outcomes of existing ABMs.

To meet this goal we address four research questions: (1) How does agents' heterogeneity in incomes or in locational preferences affect emergent land-use patterns? (2) How does the magnitude of heterogeneity in agents' population affect spatial and economic phenomena? (3) Do the collective effects from multiple sources of agent heterogeneity vary under different market representations? and (4) Are different representations of market elements able to reconcile some conflicting results about the effects of agent heterogeneity drawn by other models? The paper is organized in the following way. Section 2 provides an overview on modeling agent heterogeneity and land markets with ABMs. Section 3 presents the stylized ABLMM and the settings for the experiments design to explore the effects of agent heterogeneity under four market representations. In Section 4, results of different experiments are compared. Finally, Section 5 provides the general conclusion and discussion.

2. ABM and heterogeneity: a brief overview

Spatially explicit ABM is widely used for simulating complex urban land-use change phenomena, including residential choice (Brown et al., 2008; Kii & Doi, 2005; Ligmann-Zielinska, 2009; Torrens, 2007), social-economic segregation (Benenson, 1998; Benenson, Omer, & Hatna, 2002; Crooks, 2006; Feitosa, Le, & Vlek, 2011; Fossett & Waren, 2005; Jayaprakash, Warren, Irwin, & Chen, 2009; O'Sullivan et al., 2003), gentrification (Diappi & Bolchi, 2008; Jackson, Forest, & Sengupta, 2008; O'Sullivan, 2002), verification of location theory (Sasaki & Box, 2003), zoning and urban planning (Ligtenberg, Wachowicz, Bregt, Beulens, & Kettenis, 2004; Zellner et al., 2010), the housing market (Ettema, 2011; Filatova, Parker, & van der Veen, 2009; Filatova, van der Veen, & Parker, 2009; Magliocca et al., 2011; Parker & Filatova, 2008) and microsimulation of urban system (Ettema, Jong, Timmermans, & Bakema, 2007; Kii & Doi, 2005; Miller, Douglas Hunt, Abraham, & Salvini, 2008; Miller, Farooq, Chingcuanco, & Wang, 2011; Waddell, 2002; Waddell, Wang, & Liu, 2008; Wagner & Wegener, 2007). Agent heterogeneity plays an important role in these models.

2.1. Heterogeneous economic agents

In a spatial land market model, agent heterogeneity refers to the differences among either characteristics of individual decision makers (e.g. preferences, incomes) or their behavioral functions (e.g. expectations formation, decisions-making strategies). The differences could be either internal (e.g. demographic and household characteristics, personal experiences, expectations, and risk attitudes) or external (e.g. social networks, accessibility to information, and policies) (Irwin, 2010; Valbuena, Verburg, & Bregt, 2008). Generally speaking, two approaches are used to introduce agent heterogeneity at model initialization. The first method is to continuously vary the agent characteristics (e.g. income, preference, etc.). For example, Benenson (1999) found continuously varying economic characteristics (e.g. income and income growth rate) will result in a relatively stable residential distribution. Filatova, Parker, and van der Veen (2011) found qualitatively different results in spatial and economic metrics in hazard-prone areas between households with heterogeneous risk perceptions based on an empirical survey distribution and homogeneous agents with risk perception equal to the average of the population.

The second method to impose heterogeneity is to divide the agents into different categories. The typology of agents could be determined by either one attribute (e.g. ethnicity) or multiple criteria (e.g. income level and neighborhood circumstance) (An, 2012). Different groups of agents could share the same decision-making function but have different parameters for the function, or they could even have different decision-making strategies (e.g. Schreinemachers & Berger, 2006). For example, Li and Liu (2007) divided households into five groups and empirically calibrated their weights on the same utility function. Satisfactory results of residential development were produced by a few groups of agents. Ghoulmie and colleagues (2005) found, in a single-asset financial market, heterogeneity of agent strategies is one of the important ingredients in reproducing some regular patterns. Magliocca et al. (2011) also used different decision making processes for developers in the formation of rent expectations and suggested the path dependence of spatial patterns has direct linkage with individual heterogeneity.

2.2. Agent heterogeneity in an agent-based land market models

Classical analytical land-market models such as the Von Thünen model (Von Thünen, 1966) and the monocentric city models (Alonso, 1964; Mills, 1972; Muth, 1969) established theoretical benchmarks for economic models of urban land-use change, e.g., the downward-sloping rent gradient, which is also seen robustly in the real world. Such analytical models, however, are of limited utility for examining spatial and agent-level heterogeneity in combination. In response, the usefulness of spatially explicit ABMs that contain land market representations has been emphasized by reviews (Haase & Schwarz, 2009; Irwin, 2010; Irwin & Geoghegan, 2001; Ligmann-Zielinska & Jankowski, 2007; Parker & Filatova, 2008); however, ABMs that have a representation of an explicit land market remain relatively rare. A subset of these models has enabled researchers to extend these classical models to directly simulate individual's behavior in a land market, replicating the classical results as a model verification exercise (Chen, Irwin, & Jayaprakash, 2011; Filatova et al., 2009).

The importance of ABLMM in understanding the effects of agent heterogeneity on the processes and patterns of LUCC can be summarized in several aspects. First, ABLMM provides a more flexible platform that needs fewer assumptions and restrictions compared to traditional economic models. As discussed in greater detail in Section 2.3, models can embrace agent heterogeneity rather than use a representative agent, and focus more on the

Table 1
Agent heterogeneity and market levels in representative models.

Market level	Bidding	Budget constraint	Agent heterogeneity		Representative models
			Preference	Budget	
L0	No	No	No	No	Standard CA
			Yes	No	SOME, Brown et al. (2004, 2006) and Zellner et al. (2010)
			No	Yes	Benenson (1998, 1999)
L0.5	Yes	No	No	No	Ligmann-Zielinska (2009)
			Yes	No	Ligmann-Zielinska (2009)
L1	No	Yes	No	No	CA model with threshold of land use change
			Yes	Yes	GA Torrens (2007)
L2	Yes	Yes	No	No	CA model with multiple land uses
			Yes	Yes	ALMA-C (Filatova et al., 2009); CHALMS (Magliocca et al., 2011)

out-of equilibrium dynamics rather than on the equilibrium per se (Arthur, 2005; Hommes, 2005; Kirman, 1992; Tesfatsion, 2006). Second, in addition to the aggregated spatial patterns and economic metrics, ABLMM generates heterogeneous information at the individual level (e.g. agent's preference and pricing information). This additional information can provide various measurements (e.g. segregation index, sprawl measurement, and rent gradients) to compare with empirical findings or theoretical studies and enrich our understanding of the process of LUCC and its consequences. Third, it serves as a laboratory to test some hypotheses about effects of agent heterogeneity in land-use simulations. On the one hand, empirical data can be used in an ABLMM to replicate the LUCC trajectory; on the other hand, theoretical models can help researchers find out what kinds of data should be collected to parameterize empirical information into the model.

We identify three critical elements of the land-market process: preferences, budget constraints, and competitive bidding (Parker et al., 2012). Building upon these three, Table 1 divides the market mechanisms into four levels, and then compares the market representations and agent heterogeneity realized in the representative models mentioned above.

- In market level 0, agents make residential choice based on preferences without budget constraints or competitive bidding. Representative applications are the SOME model developed by Brown, Page, Riolo, and Rand (2004, 2006) and the model developed by Benenson (1998, 1999). The agents are potentially heterogeneous in their preference for residential density in the former model and in the latter model their budgets are potentially heterogeneous.
- In market level 0.5, competitive bidding is added. A representative model is developed by Ligmann-Zielinska (2009), which simulates the developer's bidding behavior with heterogeneous risk attitudes.
- Budget constraints for buyers are represented in market level 1. The geographic automata model developed by Torrens (2007) is an example.
- In the last level, market level 2, both competitive bidding and budget constraint are included. The ALMA-C (Filatova et al., 2009) model and CHALMS model (Magliocca et al., 2011) have the functionality to simulate both mechanisms.

It is evident that the market representations are different for these representative models. However, none of these models is able to fully examine the effects of agent heterogeneity across all these market representations.

2.3. Effects of agent heterogeneity

The ability to incorporate agent heterogeneity is one of the main reasons why ABM is attractive to both economists and geographers. For economists, an ABM provides a platform that could relax the assumptions and restrictions on traditional economic models (Arthur, 1999; Arthur, 2005; Tesfatsion, 2006). Traditional economic models usually adopt a representative agent and assume a static equilibrium condition. However, in real conditions, agents are inherently different in their demographic and socioeconomic characteristics and therefore have different actions, strategies and expectations in their decision-making (Arthur, 2005; Axtell, 2000; Axtell, 2003; Epstein, 1999; Farmer & Foley, 2009; Hommes, 2005; Tesfatsion, 2006). Substitution of heterogeneous agents by a representative one in a model may result in failure to simulate realistic macro-pattern and misrepresent the response to a policy measure (Kirman, 1992). Counter-intuitively, in some cases, an increase of agent heterogeneity has the effect of producing regular and stabilizing results. In Kirman's review (1992), an increase in the heterogeneity of income or preference may give rise to a smooth aggregated demand pattern. For geographers, an ABM provides a more powerful tool to simulate the heterogeneous interactions between human and natural systems than traditional modeling approaches which have not represented decision makers. Unlike CA models which solely rely on the historical and neighborhood spatial heterogeneity, ABMs introduce heterogeneous decision makers (Macy & Willer, 2002). Increasingly, more researchers have found that the agent heterogeneity is a driving force for landscape change. By allowing the inclusion of agent heterogeneity, emerging landscape patterns and LUCC phenomena, for

Table 2
Key input parameters for the LUXE model.

Parameter	Meaning	Values
Constant Parameters		
S_L	Size of the square landscape	61
N_b	Number of household buyers	400
N_s	Number of rural land sellers	3721 (61×61)
$\delta\beta$	The range of β utility calculation, beta will be bounded by $[\beta - \delta\beta/2, \beta + \delta\beta/2]$	0.20
b	Budget splitting factor	0.6
t	Unit transport cost	1.00
$\bar{B}$	Mean housing budget for buyers	160
r_N	The size of a rook neighborhood in the calculation of open space amenity	2
$\bar{\beta}$	Mean value of preference for proximity in utility calculation	0.5
N_{sp}	The number of parcels that a buyer evaluate for bidding	4000
Market level Parameters		
WTA	Agricultural reservation price	0, 100
$N_{bd}^{\max}$	Number of bids allowed for one parcel, one means no bidding	1, 400

Market level 0: WTA = 0 and $N_{bd}^{\max} = 1$;
Market level 0.5: WTA = 0 and $N_{bd}^{\max} = 400$;
Market level 1: WTA = 100 and $N_{bd}^{\max} = 1$;
Market level 2: WTA = 100 and $N_{bd}^{\max} = 400$.

Table 3
Values of the parameters in the three experiments.

	Standard deviation of preference	Standard deviation of budget
Experiment 1	0	0
	0	30
	0.3	0
Experiment 2	0.1, 0.2, 0.3, 0.4, 0.5	0
	0	10, 20, 30, 40, 50
Experiment 3	0.1, 0.2, 0.3, 0.4, 0.5	10, 20, 30, 40, 50

example, urban sprawl, urban gentrification, residential segregation, and locational choice of residents and firms, can be simulated from bottom up (Benenson & Torrens, 2004).

Even though the importance of agent heterogeneity is emphasized by researchers, systematic investigations of the effects of agent heterogeneity are rare. This gap is important for various reasons. First of all, many existing models have a single heterogeneous characteristic and focus on either spatial or socioeconomic outcomes. In reality, however, agents differ from each other in several characteristics, each of which might have similar effects. For instance, heterogeneous preferences for open space amenity, lifecycle events and income heterogeneity could lead to leapfrog and fragmented patterns (urban sprawl) as well as income segregation (An, Brown, Nassauer, & Low, 2010). Further, using only one heterogeneous characteristic excludes the interactions between different heterogeneous characteristics. Studies show the collective effect of multiple sources of agent heterogeneity affects the performance of model substantially. For instance, in the segregation model, Benenson (1999) found variation of economic status and cultural diversity has complicated effects on the stability and segregation of cultural groups. In a land-market model, Magliocca et al. (2011) found interactions between heterogeneity in preference for housing types and income will lead to a sprawling development in ex-urban area.

Second, the effects of magnitude of agent heterogeneity on model outcomes are uncertain. For instance, Brown and Robinson (2006) used the SOME model to show that the presence of preference heterogeneity will lead to more sprawl regardless of the magnitude of preference heterogeneity. In contrast, Ligmann-Zielinska (2009) found the preference for specific criterion (e.g. attractiveness or price) has dominant effect on the spatial distribution of development, and the level of compact development are significantly different when the representative developer changes his risk attitude. But the effects are negligible when there are multiple developers with combinations of heterogeneous risk attitudes. The open question is, does the spatial pattern vary monotonically with an increased magnitude of agent heterogeneity, or do multiple sources of agent heterogeneity have nonlinear effects on the outcomes?

Third, inconsistent conclusions on the effect of agent heterogeneity are drawn by different models. For example, Brown and Robinson (2006) have used survey data in the SOME model to show that adding preference heterogeneity to agents will result in more sprawling and fragmented development. However, in a latter study based on the same model, Zellner et al. (2010) found that the effect of incorporating heterogeneous preference is not uniform. More specifically, heterogeneity will induce compact development when most households have higher preference for density but sprawling development when the mean of density preference is low. Using another model, Ligmann-Zielinska (2009) found that the land-use pattern is slightly less compact when the developers have heterogeneous risk attitudes. Filatova et al. (2009) found that agents' heterogeneous risk attitudes will lead to more developments in the coastal area, which has a higher level of amenities and is far from city center, even under budget constraint and competitive bidding. It is clear that these conflicting conclusions are drawn by different models with different representations of market processes (Table 1). Evaluating the effect of agent heterogeneity across different levels of market representation gives us opportunity to reconcile these inconsistent conclusions.

In summary, although most researchers agree on the importance of agent heterogeneity and represent it to some extent, the effects of varying multiple sources of agent heterogeneity are not systematically inspected, and the conclusions drawn are inconsistent. In addition, a considerable number of models have more than one source of agent heterogeneity[3]. The open question now is to what extent the agent heterogeneity, magnitude of agent heterogeneity, and interaction of multiple sources of agent heterogeneity (e.g. budget and preference), will affect spatial and socioeconomic outcomes. A corollary question is whether differences, if found, can reconcile the inconsistent conclusions drawn by different models with market representations. Our stylized ABLMM, LUXE, allows us to explore these research questions through its ability to accommodate multiple sources of agent heterogeneity and to evaluate the effects across different levels of market representation at the aggregated level and individual level.

3. Model description and scenario setting

The LUXE model belongs to the SLUCE II (Spatial Land Use Change and Ecological Effects) project, which is a part of a larger modeling effort that integrates land use and land management dynamics as well as ecosystem services processes (Robinson et al., 2010). A more detailed description of the model can be found in Parker et al. (2012).

3.1. Model description

Space in LUXE is divided into a rectangular lattice of congruent cells. Each cell is either agricultural land or residential land. There is a CBD (central business district) centered in the lattice. No other public facilities, i.e. road network, school, or hospital, are represented.

Two types of agents are simulated in the model. Sellers are the owners of land who put their lands in the market, receive and evaluate a number of bids from buyers, and sell the land to the highest bid, provided it is larger than their expected prices (i.e., willingness to accept, WTA). The second type of agents are buyers, who are households looking for residential land. Every buyer evaluates a number of parcels and forms a utility based upon spatial characteristics and individual preference given by a Cobb–Douglas form[4]:

$$U = A^{\alpha} \cdot P^{\beta} \tag{1}$$

where U denotes utility; A stands for measure of open space amenity, which is the residential density in a Moore neighborhood.[5] P

[3] In a review on the urban residential choice models based on ABM, among the 51 reviewed models, 36 of them have agents with more than one source of agent heterogeneity (Huang, Parker, Filatova, & Sun, accepted for publication).

[4] LUXE combines the features of two existing models, ALMA and SOME, which are also based on the Cobb–Douglas form of utility calculation. The Cobb–Douglass functional form is a standard in economics, allowing easy comparison to other work. However, the form has acknowledged limitations, such as optimally allocating a fixed share of the buyer's budget to each good, regardless of their income level. In this model, the buyer's willingness to pay reflects their demand for a bundle of goods' attributes—proximity and amenities. In the real world, relative expenditures to these two factors might vary as income increases or decreases. Therefore, although we used the Cobb–Douglass functional form here to maintain comparability to previous work, some results of the effect of budget heterogeneity might be modified using a more flexible functional form. This would be a valuable extension for future work.

[5] In this paper, the neighborhood size is set to 2 (i.e. nearest 24 neighbors surrounding a host cell in a 5 by 5 neighborhood), because a neighborhood size larger than 2 is prone to induce a fragmented landscape and smaller ones encourage infill development.

Table 4
Experiment 1: agent heterogeneity parameters and output metrics (average and standard deviation values out of 40 repeated runs) under four market levels.

Level	SDP	SDB	MTC	TDP	ED	MU	MTP	Theil
L0	0	0	10.39$^{n/a}$ (0.06)	400$^{n/a}$ (0)	2.62$^{n/a}$ (0.06)	0.84$^{n/a}$ (0.00)	98.88$^{n/a}$ (0.06)	N/A
	0.3	0	9.52*** (0.13)	400$^{n/a}$ (0)	2.19*** (0.08)	0.87*** (0.00)	101.94*** (0.10)	N/A
	0	30	10.39 (0.06)	400$^{n/a}$ (0)	2.62 (0.06)	0.84 (0.00)	98.66 (1.19)	0.02*** (0.00)
L0.5	0	0	10.39$^{n/a}$ (0.05)	400$^{n/a}$ (0)	2.63$^{n/a}$ (0.06)	0.84$^{n/a}$ (0.00)	98.87$^{n/a}$ (0.05)	N/A
	0.3	0	10.13*** (0.22)	400$^{n/a}$ (0)	2.46*** (0.10)	0.86*** (0.00)	100.93*** (0.16)	N/A
	0	30	10.39 (0.05)	400$^{n/a}$ (0)	2.63 (0.06)	0.84*** (0.00)	99.40*** (1.20)	0.02*** (0.00)
L1	0	0	6.75$^{n/a}$ (0.05)	160$^{n/a}$ (2)	2.71$^{n/a}$ (0.07)	0.89$^{n/a}$ (0.00)	105.07$^{n/a}$ (0.10)	N/A
	0.3	0	8.14***	281*** (5)	2.22*** (0.08)	0.89*** (0.00)	104.65*** (0.10)	N/A
	0	30	8.61*** (0.15)	238*** (9)	2.90*** (0.08)	0.87*** (0.00)	115.32*** (0.90)	0.01*** (0.00)
L2	0	0	6.76$^{n/a}$ (0.04)	161$^{n/a}$ (2)	2.71$^{n/a}$ (0.06)	0.89$^{n/a}$ (0.00)	105.04$^{n/a}$ (0.12)	N/A
	0.3	0	7.50*** (0.11)	233*** (4)	2.28*** (0.08)	0.90*** (0.00)	105.34*** (0.09)	N/A
	0	30	8.61*** (0.46)	252*** (19)	2.75** (0.06)	0.87*** (0.00)	114.31*** (1.86)	0.01*** (0.00)

SDP: standard deviation of preference for city center proximity; SDB: standard deviation of budget; MTC: mean transport cost; TDP: total developed parcels; ED: edge density; MU: mean utility; MTP: mean transaction price; Theil: Theil index based on budget spatial distribution.
*Significant at 0.1, **0.01, and ***0.001 with Wilcoxon Signed-Rank Test and a null hypothesis that metrics have the same distribution between scenario with heterogeneous agents and scenario with homogeneous agent under each market level (n/a: cannot compute with ties; N/A: Theil index cannot be computed when buyers' budgets are homogeneous).

is the proximity to the CBD, which is standardized by the distance to the CBD (d). The distance is measured in Euclidean distance. Both A and P range from 0 to 1; α and β are the weights for A and P respectively and $\alpha + \beta = 1$.

Buyers form their ask price (willing to pay, WTP) based on the utility and available budget and transport cost (Filatova et al., 2009).

$$WTP = (B - t \cdot d)\frac{U^2}{b^2 + U^2} \tag{2}$$

where B stands for the individual budget, and $t \cdot d$ is the transport cost to the CBD which is a linear function of d, the distance to the CBD, and t, the transport cost per unit of distance, is set to 1. U is the utility from Eq. (1) and b is a constant that represents the affordability of all the other non-housing goods. The chosen WTP function is consistent with the previous ALMA model (Filatova et al., 2009) and reflects the main qualitative properties of the neoclassical demand function.

The model starts with initialization of the CBD at the center of the space. Sellers are initialized with a fixed and homogenous WTA for every cell. Then a number of buyers are generated with potentially heterogeneous budgets and preferences. All sellers put their properties on the market, and buyers evaluate all the properties and bid on the one with the maximum utility. This implies the buyer will bid on the most desirable cell over the whole space. Sellers receive a number of bids via the market and decide whether to accept or reject the bid based on different rules under different market levels (explained in Section 3.2). A successful transaction is registered if the seller agrees to sell the parcel and the land cell is converted to residential. In this case, the transaction price is equal to buyer's WTP. Failed buyers re-enter the market at the next step. Thus, each run of model may contain multiple steps. Finally, a market clearing condition is reached when no more transaction can be made. Essentially, this final result replicates a static economic equilibrium in the land market.

3.2. Market levels

In order to explore the effects of agent heterogeneity under different market representations, four levels of market representations are designed (see Table 1). The parameters setting for each market level is explained in Table 2.

- Market level 0 (L0) is the most primitive scenario, without budget constraints and competitive bidding. Therefore, the agricultural reservation price (WTA) and number of bids allowed for one parcel are set to 0 and 1 respectively. In other words, each buyer in market level 0 will sequentially choose the parcel with the highest utility in a first-come first-serve way.
- In market level 0.5 (L0.5), competitive bidding is added but a budget constraint is still missing. It implies that the buyers can compete for the same parcel, and the one with the highest bid will get that parcel.
- In market level 1 (L1), a budget constraint is added, but competitive bidding is suppressed. That means that buyers will only get the parcel if their WTPs are higher than sellers' fixed WTA.
- Both competitive bidding and budget constraints are represented in market level 2 (L2). This implies that buyers will bid on the land, and the seller will accept the highest bid only if the maximum bid is larger than the WTA.

Under the four market representations, we design three series of experiments to answer the three questions mentioned above with regard to the effects of agent heterogeneity on the spatial and socioeconomic outcomes.

3.3. Model setup

Table 2 lists all the parameters used in the experiments for this paper. Experiments are carried out in a square lattice of 61 * 61 cells[6] initially. Every cell is occupied by a seller, and therefore there are 3721 sellers. The number of buyers is 400 at model

[6] Our goal in setting the landscape size was to choose a landscape that was sufficiently large for robust experimentation, but small enough to maintain computational tractability. We determined that the 61 * 61 cell landscape is sufficiently large because: (1) Recalling that this is essentially an open city model, all buyers who wish to purchase parcels in each run are able to locate (equivalently, the landscape is large enough to reach equilibrium). (2) The range of urban development in each equilibrium is well within the landscape boundary, causing no edge or boundary effects. (3) Under current parameter settings with 400 buyers, no buyer would choose a cell beyond their current range as it would invoke a higher transport cost. (4) Although the actual landscape metrics would differ slightly in a larger landscape due to smoothing effects, the standard deviations of all these metrics across 40 repetitive runs are relatively small (Table 4), which indicates the results are stable and sufficient to represent the individual-level processes that drive land transition with agent heterogeneity. (5) Finally, the standard deviations of socioeconomic metrics are also small, and the number of observations is sufficient to provide econometric rent gradient estimates with high significance levels and goodness of fit.

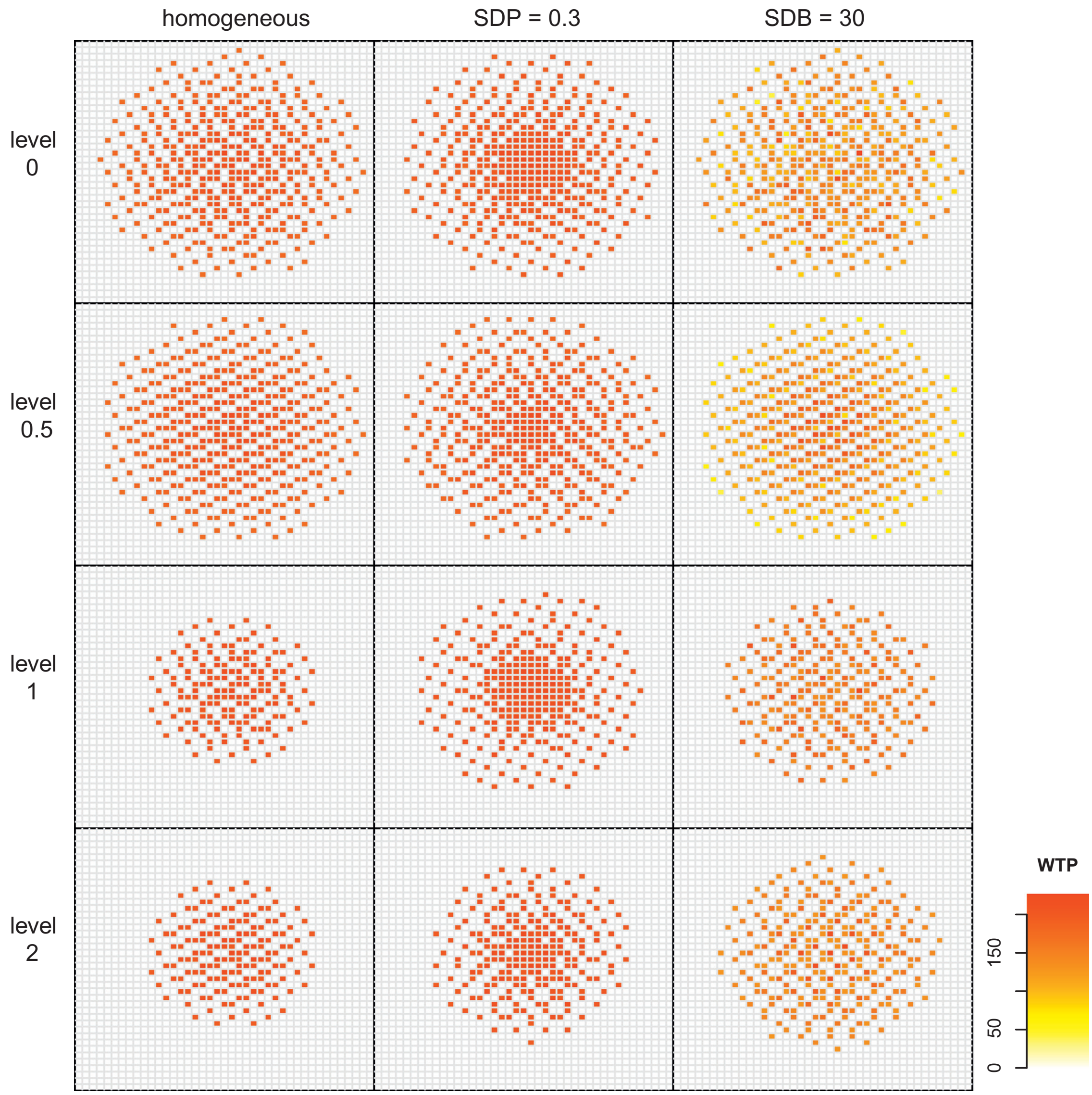

Fig. 1. Experiment 1: land use change and transaction prices between scenario with homogeneous agents and scenario with heterogeneous agents across four market levels (all these plots are from the first of 40 repeated runs, SDP: standard deviation of preference for city center proximity, SDB: standard deviation of budget).

initialization. Their budgets and preferences are set according to their mean and standard deviations under different experiments (see Section 4 for details). In order to guarantee that the experiments with heterogeneous agents are comparable to the ones with homogeneous agents, the preference and budget follow a stochastic distribution with equal mean values but different standard deviations.

3.3.1. Model validation

ABMs face the difficulty in model validation (Manson, 2002; Ngo & See, 2012; Parker, Berger, & Manson, 2002). The goal of validation is to compare the model outcomes to independent data and expectations and to measure the agreement between them (Manson, 2002). Manson (2002) divided validations into two types: structural validation and outcome validation.

Structural validation measures how well the model represents the theoretical mechanisms of real-world phenomenon (Manson, 2002). In LUXE, structural validation is performed by replicating the classical outputs of the monocentric model (i.e., a downward slope of land prices from the urban center), similar to the ALMA model (Filatova et al., 2009). In addition, a large range of input parameters are swept to guarantee model outcomes are consistent with theoretical expectations (Sun et al.,accepted for publication). In this stage, the agreement between model outcome and theoretical patterns are measured by qualitative and visual interpretation.

Outcome validation measures how well the model outcomes conform with empirical data (Manson, 2002). Currently the LUXE model is a highly stylized ABM. However, the final stage of the SLUCE II model will be equipped with empirical data. It can be validated by comparing model outcomes to real-world data in both spatial and nonspatial dimensions, for example, quantity and patterns of land-cover change, land-management change, land and housing prices, and carbon exchange and storage, which also suggests that the output validation requires extensive data from census, remotely sensed images, and household surveys as well as field surveys.

3.4. Output measurement

Traditionally, spatial land-use change model outcomes are analyzed by landscape metrics, which are derived from landscape ecology and used for measuring landscape patterns, such as

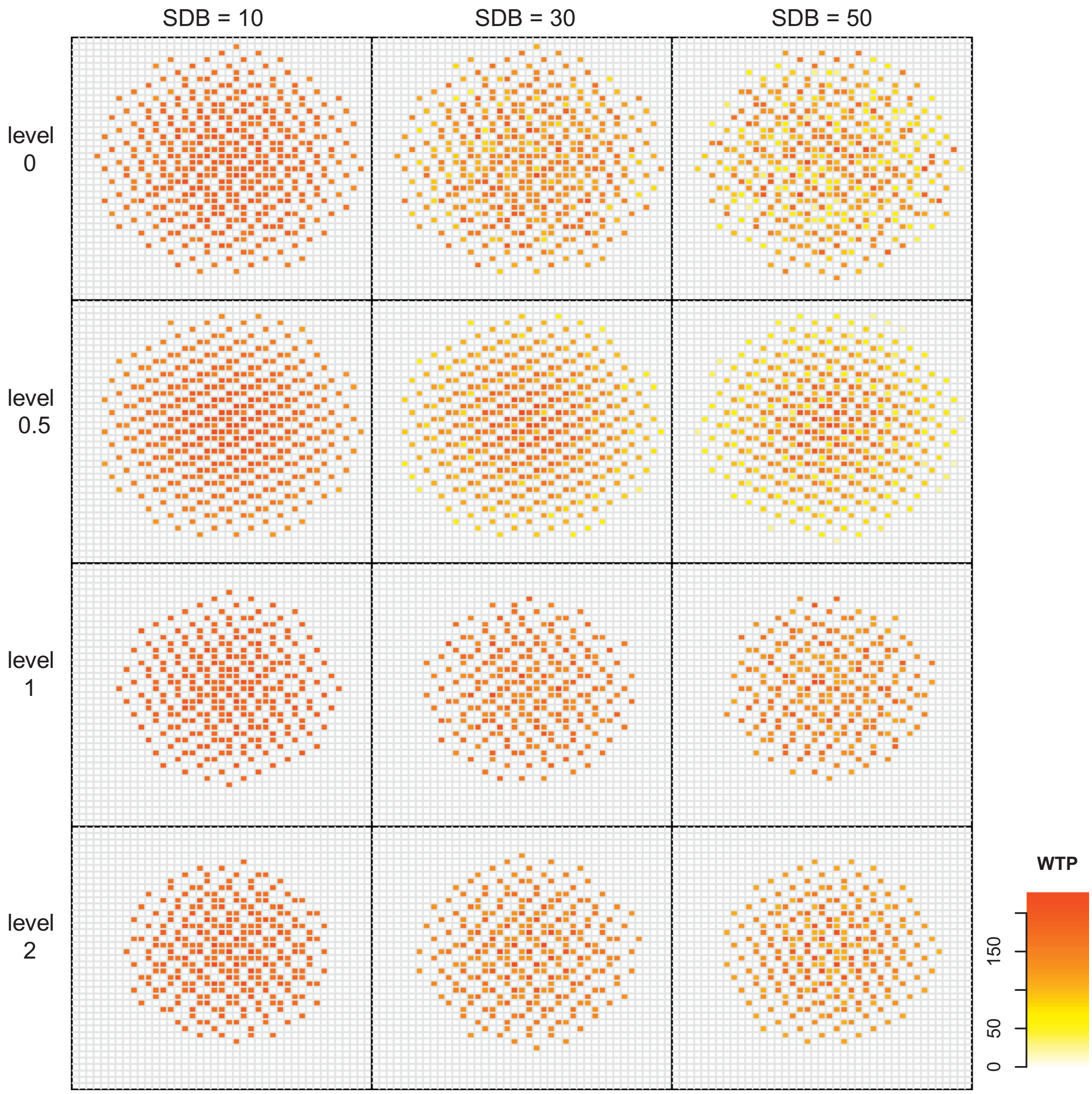

Fig. 2. Experiment 2: land use change and transaction prices with increasing degree of budget heterogeneity across four market levels (all these plots are from the first of 40 repeated runs, SDB: standard deviation of budget).

fragmentation metrics, diversity metrics (Brown et al., 2004; Irwin & Bockstael, 2002; Parker & Meretsky, 2004), and segregation metrics (Benenson, 1998; Fossett & Waren, 2005; Jayaprakash et al., 2009; Omer, 2005; Schelling, 1971). However, a land market model can provide economic as well as spatial outcomes. Hence, two groups of metrics are used to evaluate the model outcomes. The first group includes three landscape metrics, which measure the spatial patterns of land use change. First, the total developed parcels (TDP) records how many parcels are converted from agriculture to urban land. Second, edge density (ED) measures the edge characteristics of land-use change. It varies from 0 to 1, and a smaller value indicates a more compact pattern. Mean transport cost (MTC) indicates the average range of urban development.

The second group of metrics concerns socio-economic patterns at the agent level. Mean transaction price (MTP) and mean utility (MU) measure the land price and satisfaction of agents at an aggregated level. An evenness metric, Theil index, is used to measure wealth inequality (i.e. budget in this paper). The Theil index is calculated as:

$$Theil = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i}{\bar{x}} \cdot \ln\frac{x_i}{\bar{x}}\right) \quad (3)$$

where x_i is the budget for agent i, and N is the number of final transactions, and $\bar{x}$ denotes the mean budget of all the transactions. This index varies from 0 to ln$N$, where 0 indicates an equal distribution of income and ln$N$ indicates the maximum inequality, with one agent having all the income. This index measures the evenness of budget for all the successfully transactions. Therefore it will not vary between market levels L0 and L0.5 since all the buyers can find a parcel. But it will change in market levels L1 and L2 because only some buyers can afford a parcel under their budget constraints.

Furthermore, due to the random process and uncertainty in the model, 40 repetitive runs are used to generate outcomes for each parameter setting, to guarantee the stability of results. The results of metrics are reported by their mean and standard deviation values.

4. Experiments and results

Three series of experiments are designed to explore the effects of multiple agent heterogeneity across the four market levels. Table 3 lists the parameters for the three experiments. The first experiment is designed to explore the first question: *How does agents' heterogeneity in incomes or in locational preferences affect*

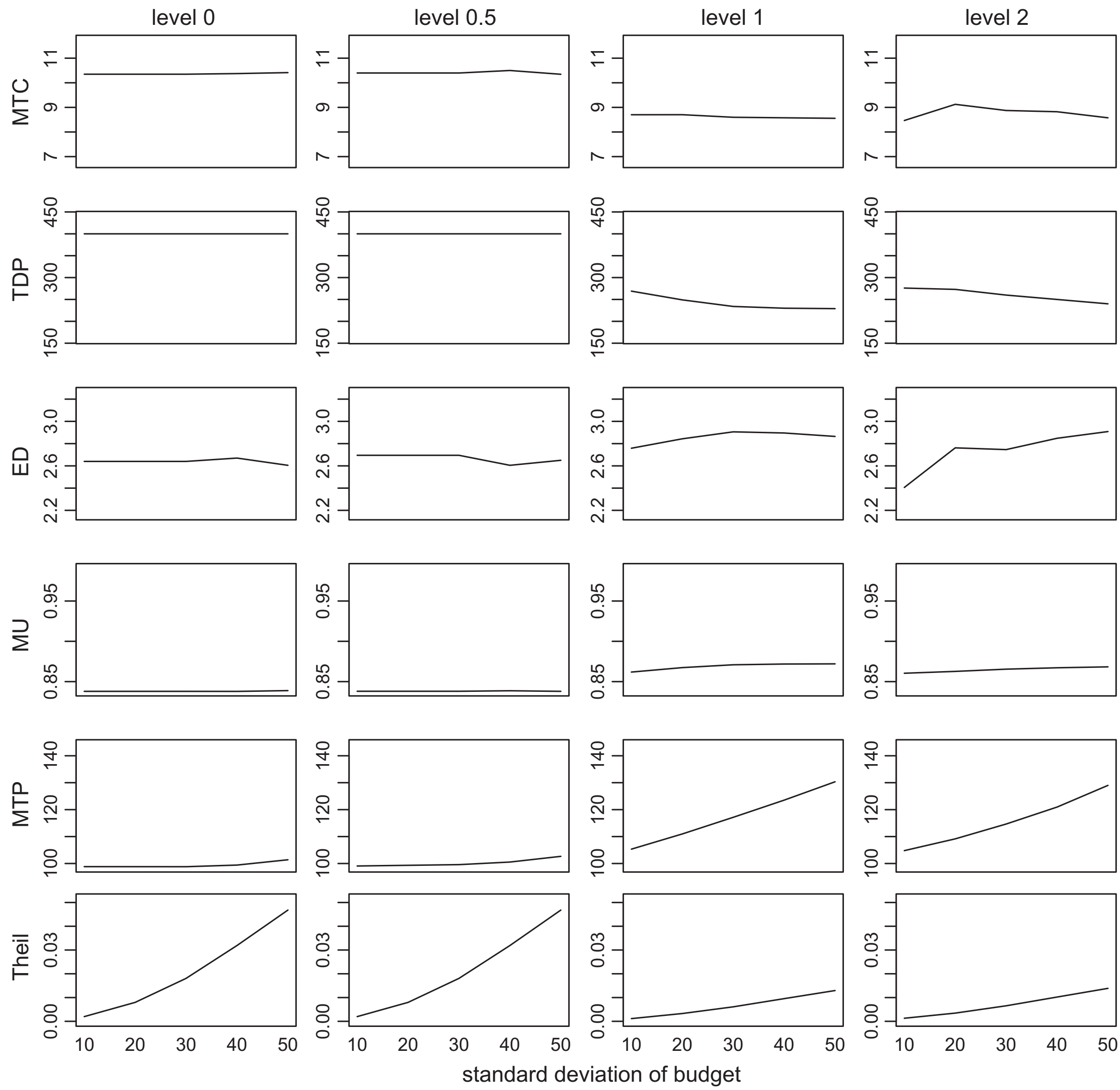

Fig. 3. Experiment 2: comparison of metrics with increasing degree of budget heterogeneity across four market level (average value across 40 repeated runs, MTC: mean transport cost; TDP: total developed parcels; ED: edge density; MU: mean utility; MTP: mean transaction price; Theil: Theil index based on budget spatial distribution).

emergent patterns? The results are compared between homogeneous agents and agents with either heterogeneous budgets or heterogeneous preferences (i.e. when agents have heterogeneous budgets, their preferences are fixed and vice versa). The second experiment is designed to answer the question: *How does the magnitude of heterogeneity in agents' population affect spatial and economic phenomena?* More specifically, *does the spatial and socioeconomic outcome vary monotonically with the increasing degree of agent heterogeneity?* Like the previous experiment, only one type of agent heterogeneities (either budget or preference) is changed while the other one remains constant. However, a broader magnitude of heterogeneity is investigated. Specifically, five gradations of heterogeneity in budget or preference are analyzed by gradually increasing the standard deviations of budget or preference (Table 3). Unlike the former two experiments, the last experiment changes budget heterogeneity and preference heterogeneity simultaneously. The collective effects of multiple sources of heterogeneity are compared to answer the question: *Do the collective effects from multiple sources of agent heterogeneity vary under different market representations?* By analyzing the results across the four market levels, the findings answer the question: *Is the representation of market elements able to reconcile some conflicting results about the effects of agent heterogeneity drawn by other models*?

4.1. Experiment 1: Heterogeneous preferences or budgets

In this experiment, agent heterogeneity is introduced by introducing the standard deviation of either preference or budget but keeping the mean values constant (see table 3). Table 4 compares the average and standard deviation values of six metrics between homogeneous and heterogeneous agents across four market levels. It also reports the significance level of the Wilcoxon Signed-Rank Test, which tests whether the measures between heterogeneous agents and homogeneous agents differ under each different market level. Fig. 1 compares the spatial development and transaction price between homogenous and heterogeneous agents.

First, consistent with existing findings (Brown & Robinson, 2006; Filatova et al., 2009; Ligmann-Zielinska, 2009; Zellner

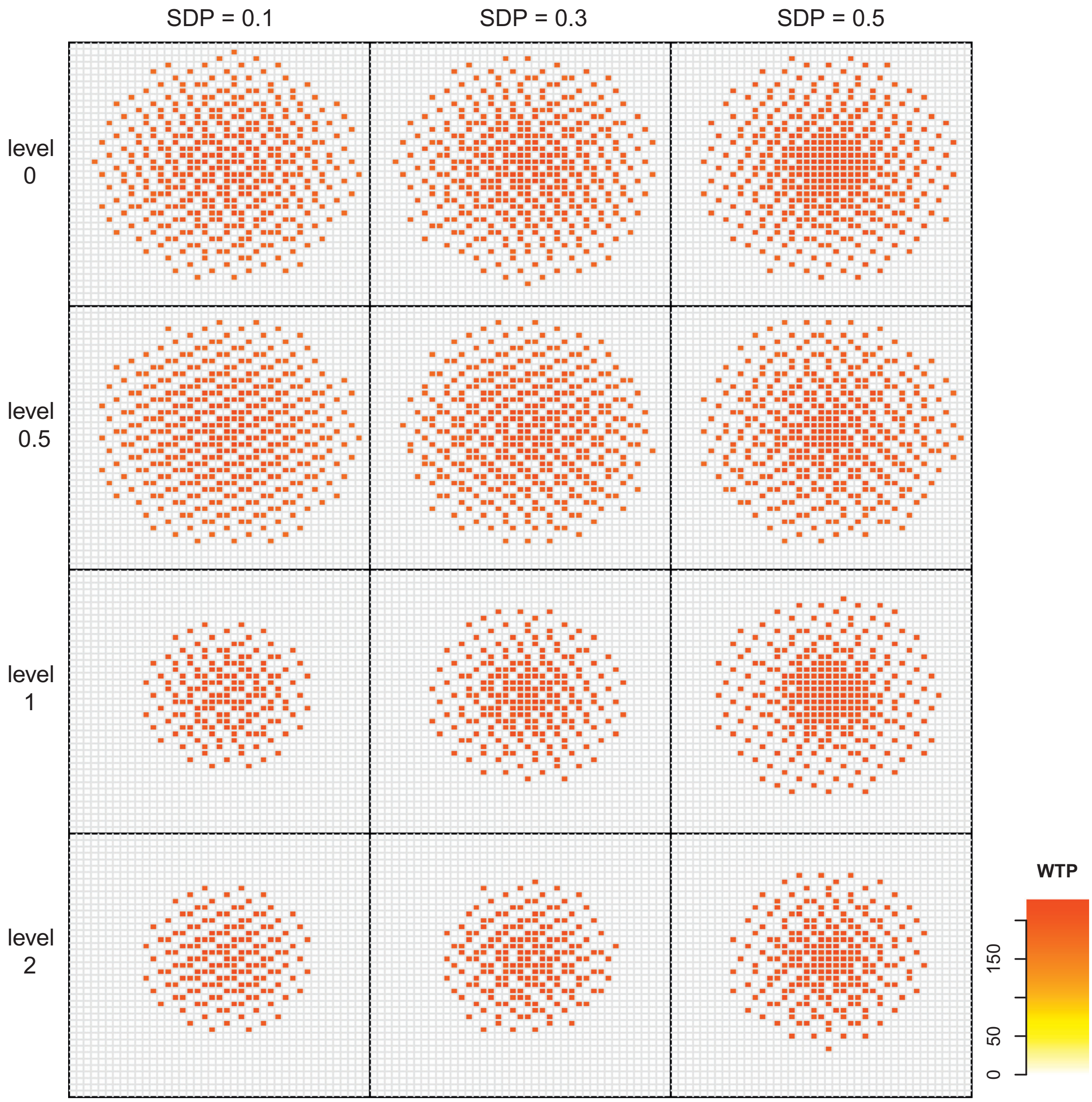

Fig. 4. Experiment 2: land use change and transaction prices with increasing degree of preference heterogeneity across four market levels (all these plots are from the first of 40 repeated runs, SDP: standard deviation of preference for city center proximity).

et al., 2010), most of measures show significantly different patterns between homogeneous and heterogeneous agents (Table 4). The difference is also evident in spatial visualizations (Fig. 1). More importantly, the results illustrate that heterogeneity in budget and preference plays very different roles in affecting the spatial and socioeconomic patterns. In contrast to the homogeneous case (the first column of snapshots in Fig. 1), preference heterogeneity leads to more compact development in the urban center (the second column in Fig. 1). Because it introduces buyers who prefer to settle down in a densely developed neighborhood in the urban center. Hence, the edge density is lower compared to the homogenous cases. Meanwhile, mean utility, the measure of buyer's satisfaction, increases in L0, L0.5 and L2, because agents with preference for either urban city or open space amenity can more easily find a parcel that gives them highest utility. Consequentially, the average transaction price increases because the WTP is highly related to the utility level (see Eq. (2)).

Intuitively, the most prominent effect of budget heterogeneity is seen in the spatial heterogeneity of transaction prices. It is obvious that the differences in the distribution of developments are less apparent than the differences in the transaction prices between homogeneous agents (the first column in Fig. 1) and heterogeneous agents (the last column in Fig. 1). This conclusion is supported by the quantitative analysis. It is evident in Table 4 that the mean transaction prices with heterogeneous budgets are 1–10% higher than in homogeneous budget case for market levels L0.5–L2. However, the difference is not statistically significant in L0 because the occupation of lands in this level follows a random first-come first-serve order. The difference resulting from either preference heterogeneity or budget heterogeneity confirms that agent heterogeneity is an important factor influencing the spatial and socioeconomic outcomes. Furthermore, the results imply that preference heterogeneity is more relevant to spatial patterns, while budget heterogeneity affects the socioeconomic patterns.

Second, market mechanisms work as an important force affecting the spatial and socioeconomic patterns. New patterns emerge between cases with homogeneous and heterogeneous agents under different market levels. For example, when budget constraints are incorporated, the mean transport cost, which indicates the range of development, reveals different results. In L0 and L0.5 (without budget constraints), the mean transport cost is 10.39 for homogeneous agents. It decreases to 9.52 (8%) and 10.13 (3%)

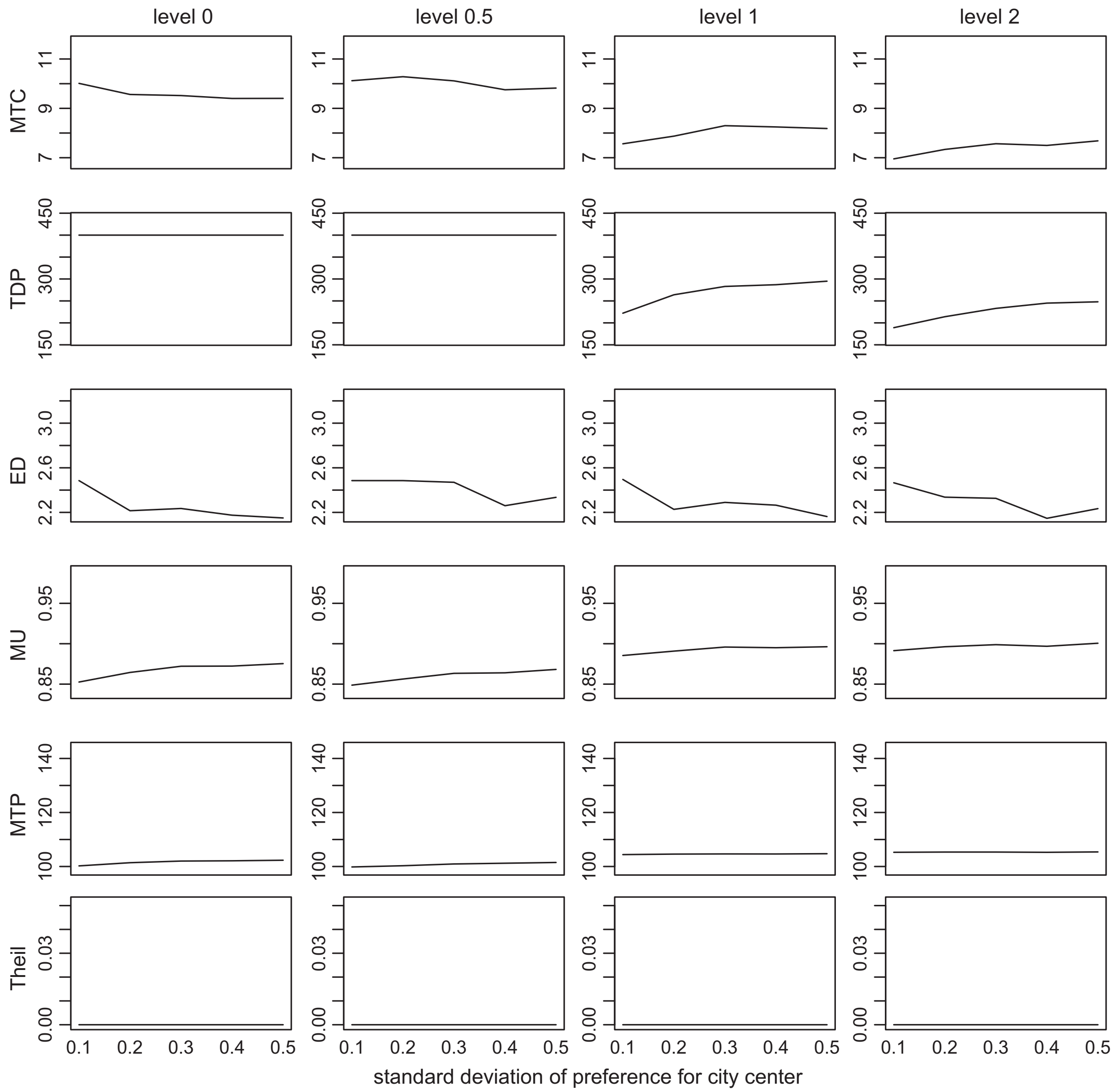

Fig. 5. Experiment 2: comparison of metrics with increasing degree of preference heterogeneity across four market levels (average value across 40 repeated runs, MTC: mean transport cost; TDP: total developed parcels; ED: edge density; MU: mean utility; MTP: mean transaction price; Theil: Theil index based on budget spatial distribution).

when buyers have heterogeneous preferences in L0 and L0.5 respectively (Table 4). That is because the compact development driven by preference heterogeneity accommodates more agents in the urban center. However, the condition is reversed in L1 and L2 (with budget constraints). Either preference heterogeneity or budget heterogeneity would result in a more dispersed development in the suburbs (Fig. 1). That is because the preference heterogeneity will introduce more buyers with higher preference for open space amenities who will have higher utility in the suburbs and can offer higher WTPs, and therefore can buy parcels in the suburbs. Meanwhile, budget heterogeneity will also introduce some affluent buyers with higher budget, and their WTP will offset the transport cost. Hence, more buyers can find a location farther from the city center than the homogeneous case. In summary, budget or preference heterogeneity will induce sprawling development in suburbs when budget constraints are incorporated, meanwhile preference heterogeneity will encourage a more compact development in the city center.

More importantly, the differences in representing the constraints and driving forces (e.g. market mechanism) shed light on conflicting conclusions drawn by different models. As discussed in the review, using the SOME, Zellner et al. (2010) found the introduction of preference heterogeneity can lead to a more compact development when the mean preference for open space amenity is high. However, Ligmann-Zielinska (2009) found the variations in risk attitudes result in a slightly less compact development. With regard to the land market elements, the difference between these two models is the latter one has the component of competitive bidding among developers. As shown in Table 1, the SOME model has neither budget constraints nor competitive bidding. The compact development drawn by the SOME model is corroborated by our model, the spatial distribution in the city center is more compact in L0 when preference heterogeneity is introduced (the first two snapshots in the first row of Fig. 1). However, the clustered city core resulting from agent heterogeneity is much smaller when competitive bidding is incorporated (the first two snapshots in the second column of Fig. 1). The result is similar to the conclusion drawn by Ligmann-Zielinska (2009) that the risk attitude heterogeneity only leads to a less clustered development. The reason is that competitive bidding, which is also represented

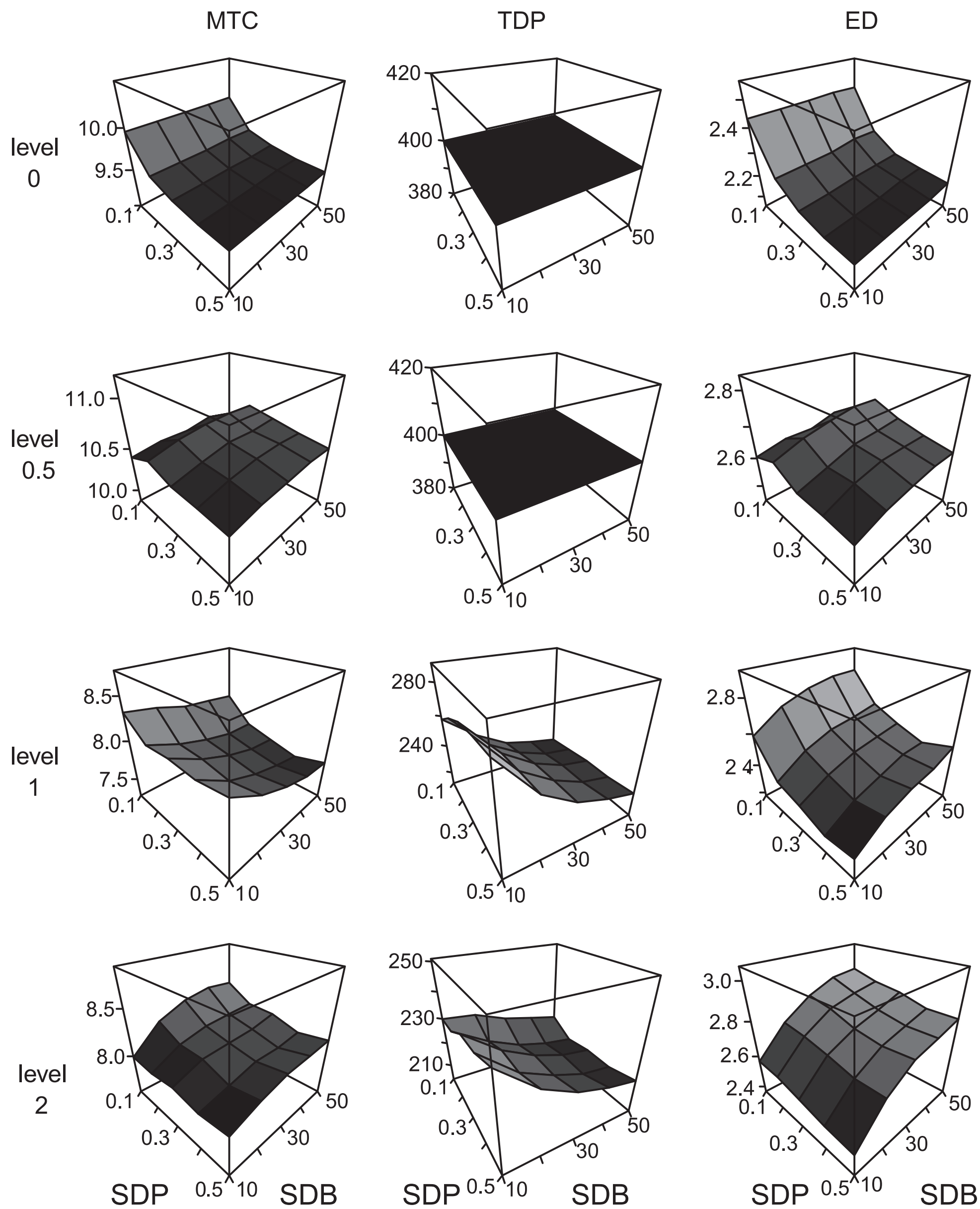

Fig. 6. Experiment 3: comparison of landscape metrics with simultaneously increasing degrees of preference heterogeneity and budget heterogeneity across four market levels. A lighter color indicates a higher value (average value across 40 repeated runs, MTC: mean transport cost; TDP: total developed parcels; ED: edge density).

in the Ligmann-Zielinska's model, enhances the challenge to successfully obtain a parcel even though preference heterogeneity gives agents opportunities to settle at the urban core as long as they outbid the others.

Third, our results show there is a tendency that, as the market representation becomes more complex, the results become more different between homogeneous agents and heterogeneous agents. With an increase of market level, more market representations are incorporated in the model; and the differences of metrics between homogeneous agents and heterogeneous agents become more statistically significant (Table 4). For instance, in L0, the differences of all the metrics between homogeneous budgets and heterogeneous budgets are not significant, but almost all of the metrics become significantly different in L2. This tendency suggests that outcomes are more sensitive to agent heterogeneity when the model becomes more complex and similar to real world. In other words, accurately representing agent heterogeneity is an important factor to make sure the model outcomes can reliably replicate empirical processes and conditions.

4.2. Experiment 2: Magnitude of agent heterogeneity

To evaluate the *impacts of variation of agent heterogeneity on the outcomes*, the second experiment sequentially increases the magnitudes of heterogeneity in budget and preference respectively (Table 3).

Figs. 2 and 4 compare the spatial patterns of development and transaction prices resulted from different degrees of heterogeneity in budget and preferences respectively across four market levels. Intuitively, the increasing degree of budget heterogeneity will lead to a greater heterogeneity of transaction prices spatially. By contrast, the increasing degree of budget heterogeneity has relatively limited influences on the spatial patterns of development. Fig. 3 compares the six metrics by increasing the degree of budget heterogeneity across four market levels. Metrics related to the spatial distribution of transaction prices, like mean transaction price and the Theil index, show monotonically increasing trends with the increasing degree of budget heterogeneity. In comparison, landscape metrics (mean transport cost and edge density) do not have

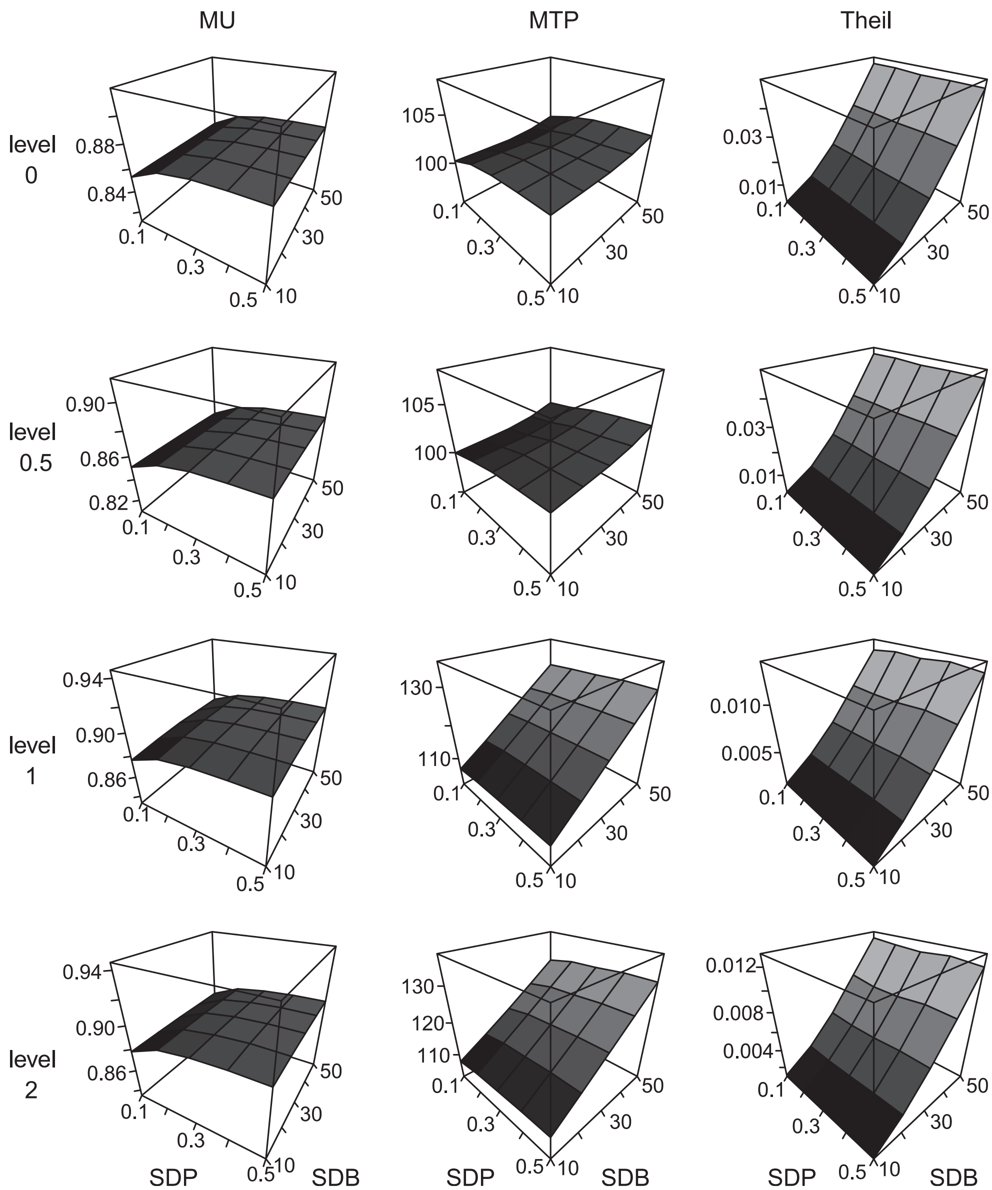

Fig. 7. Experiment 3: comparison of socioeconomic metrics with simultaneously increasing degrees of preference heterogeneity and budget heterogeneity across four market levels. A lighter color indicates a higher value (average value across 40 repeated runs, MU: mean utility; MTP: mean transaction price; Theil: Theil index based on budget spatial distribution).

a monotonic relationship with the increasing degree of budget heterogeneity. The nonlinearity can be, at least partially, explained by the differences in the representation of market process. For example, when the budget constraint is introduced, the total developed parcels will be varied with the increasing degree of budget heterogeneity (the second row in Fig. 3). Therefore, mean transport cost and edge density are not directly comparable with the increasing degree of budget heterogeneity and may show some nonlinear patterns (the first and third rows in Fig. 3).

For preference heterogeneity, the situation is reversed. Landscape metrics are more sensitive to an increasing degree of preference heterogeneity. From Fig. 4, it is clear that the increasing degree of preference for proximity to CBD will encourage compact development in the urban core. Thus, edge density decreases with the increasing degree of preference heterogeneity across four market levels. Total developed parcels is constant for L0 and level L0.5 since no budget constraint exists and all the buyers can find a land. Meanwhile, the mean transport cost decreases with the increasing degree of preference heterogeneity in these two levels because the spatial development becomes more compact. However, total developed parcels increases with the increasing degree of preference heterogeneity in L1 and L2 (Fig. 5) because, for a given budget, buyers with heterogeneous preference are more likely to find a parcel they can afford. Some of these increased developments locate in the suburbs and therefore enhance the sprawling development. The increase in mean transport cost with the increasing degree of preference heterogeneity in L1 and L2 confirms this phenomenon (Fig. 5). In summary, the increasing degree of preference heterogeneity induces more compact developments in the city center but more sprawling developments in the suburbs (Fig. 4). In addition, the non-monotonic relationship between landscape metrics (i.e. edge density and mean transport cost) and the increasing degree of preference heterogeneity is more apparent. That is because the compact development in the city center and the sprawling development in the suburbs, which is simultaneously resulted from the increasing degree of preference heterogeneity,

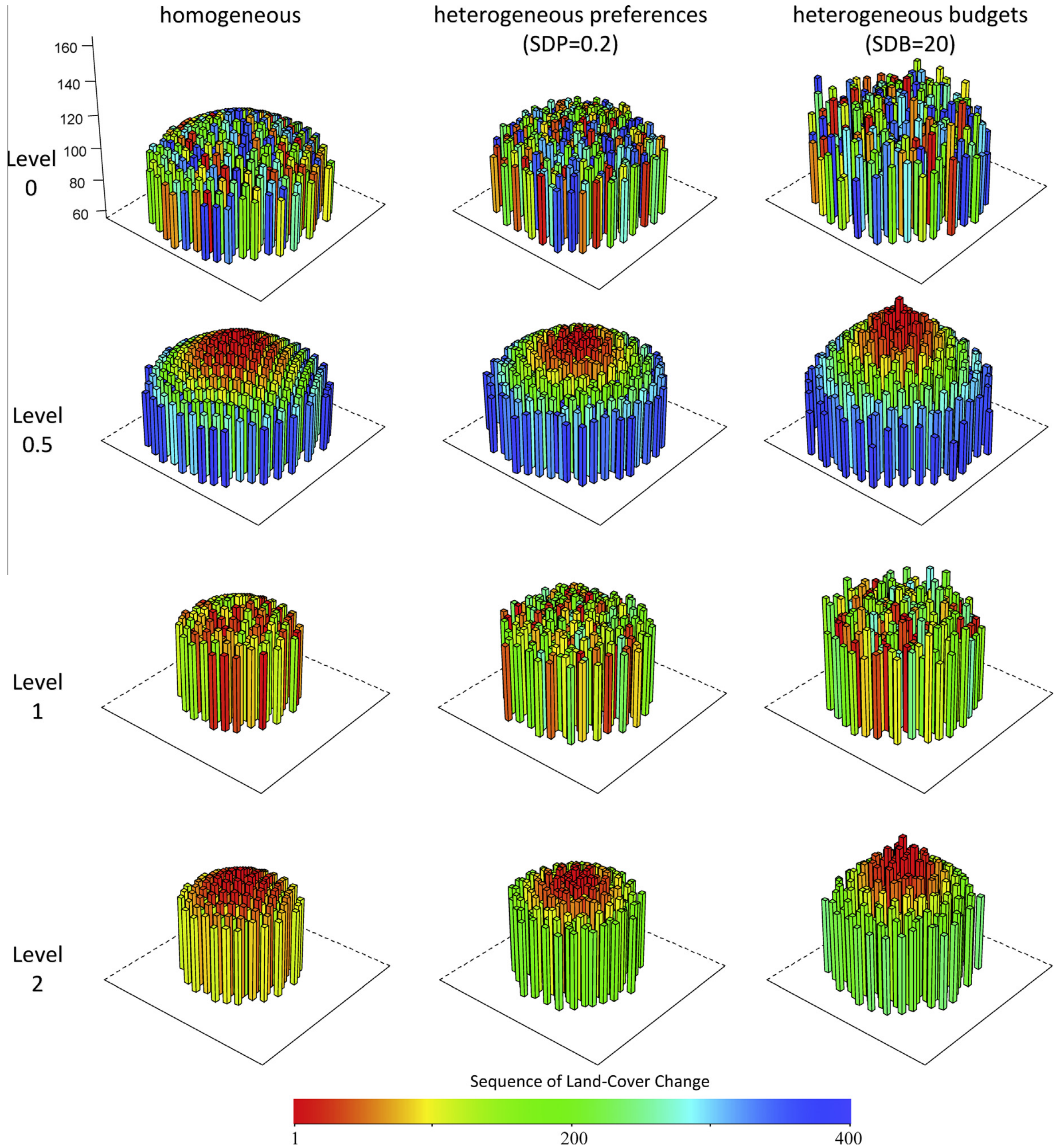

Fig. 8. Effects of market levels and agent heterogeneity on the spatial outcomes of rent gradients and sequence of land-use changes (all these 3D bar plots are from the first of 40 repeated runs. The vertical bars represent the transaction prices. SDP: standard deviation of preference for city center proximity, SDB: standard deviation of budget).

will counteract the effects of each other in calculating landscape metrics.

The results corroborate the findings from previous section: preference heterogeneity affects the spatial patterns of development (e.g. compactness of development, range of developments) but budget heterogeneity has greater impacts on individual transaction prices and the spatial distribution of transaction price. Furthermore, unlike the previous work based on the SOME model which concludes heterogeneity in agent leads to a sprawling development regardless of the degree of heterogeneity (Brown & Robinson, 2006), the results with competitive bidding and budget constraints show a more complicated pattern of development. The introduction of agent heterogeneity can result in compact developments in the city center and sprawling developments in the suburbs simultaneously. The relationship between metric and the increasing degree of heterogeneity is not uniformly monotonic.

4.3. Experiment 3: Interactions of agent heterogeneity in multiple dimensions

To understand how *the collective effects from multiple sources of agent heterogeneity vary under different market representations,* the last experiment changes the standard deviation of both preference and budget simultaneously. Figs. 6 and 7 compares the six metrics in a 3D surface with the increasing degree of both preference heterogeneity and budget heterogeneity. As discussed in the previous part, the impacts of increasing degree of agent heterogeneity could be either monotonic or non-monotonic. Hence, the collective effects from the two sources of agent heterogeneity are more complex. Generally, there are three kinds of collective effects.

First, one type of agent heterogeneity plays the dominant role in affecting the trends. For example, mean utility gradually increases with an increasing degree of preference heterogeneity across four market levels, but remains stable regardless of the increasing degree of budget heterogeneity (see the first column in Fig. 7). That is because the increasing degree of budget heterogeneity has relatively limited effects on mean utility, while the dominant influence comes from preference heterogeneity. A contrary example revealing the dominant influence of budget heterogeneity can be found in the results of Theil index (last column in Fig. 7). Obviously, increasing degree of budget heterogeneity has monotonically positive effects on Theil index across the four market levels. The increasing degree of budget heterogeneity will increase the range of transaction price and therefore intensify the wealth inequality under each market level. Since the Theil index measures the evenness of budget, it will not vary when the budget is fixed.

Second, the metrics are relatively independent to the increasing degrees of both budget heterogeneity and preference heterogeneity. For instance, the total number of developed parcels is constant in L0 and L0.5 (the second column in Fig. 6) and mean transaction price remains relatively stable in L0 and L0.5 (the second column in Fig. 7). That is because, in L0 and L0.5, all the buyers can finally find a place to live and the mean budget, which strongly relates to the transaction price, remains constant even though its standard deviation increases. In other words, the market representation is the vital force in determining the independent relationships with increasing degree of agent heterogeneity for these metrics.

Third, budget heterogeneity and preference heterogeneity have opposite effects on some metrics, and the combined effects are not monotonic. This phenomenon can be found in the variations of edge density across market levels (the last column in Fig. 6). In L0, the increasing degree of preference heterogeneity results in a monotonically more compact development. However, the influence from variations of budget heterogeneity is negligible (the first snapshot in the last column of Fig. 6), because buyers with higher preferences for urban centers are more likely to find a parcel in the center. When the competitive bidding is introduced in L0.5, the monotonic trend is interrupted. A relatively small variation of preference heterogeneity (i.e. SDP (standard deviation of preference) = 0.1) in L0.5 will not lead to a more sprawling development than a larger variation of preference heterogeneity (i.e. SDP = 0.2) as in L0 (the second snapshot in the last column of Fig. 6). That is because when the variation of preference heterogeneity is relatively small, the number of buyers getting parcels in the city center through competitive bidding is almost the same, but a relatively larger SDP (i.e. SDP = 0.2) allows for more buyers who cannot tolerate high residential density in the city center. Thus, the sprawling development is more prominent when SDP equals to 0.2 than 0.1. However, when SDP becomes even larger (SDP > 0.3), buyers with higher tolerance for crowded development will lead to more infill developments. When budget constraints are included in L1, the monotonic effect on inducing the sprawling development caused by increasing degree of budget heterogeneity becomes more prominent (the third snapshot in the last column of Fig. 6), because budget constraints allow more affluent buyers who prefer open space amenity to find parcels far from the city center. At L2, the trend is reversed from L0: the effect on edge density resulting from the increasing degree of budget heterogeneity will surpass the influence caused by the increasing degree of preference heterogeneity, and become more evident (the last snapshot in the last column of Fig. 6). The reason is that competitive bidding and budget constraints greatly enhance the possibility that buyers with higher budget and higher preference for open space amenity choose parcels in the suburban area. In the meantime, the buyers who may encourage infill developments, including buyers with lower budget and higher preference for open space amenity, or buyers with lower budget and lower preference for amenity, are more likely to fail in the process of bidding or offering a WTP larger than agricultural opportunity costs. Hence, the development becomes more fragmented.

Such findings demonstrate that the collective effects of the two sources of agent heterogeneity are complex. The results depend on the market representation and metric sensitivity to each source of agent heterogeneity. In other words, increasing degree of one type of agent heterogeneity is likely to counteract the effect of increasing variations of another type of agent heterogeneity. The result is also consistent with the conclusion drawn by Ligmann-Zielinska (2009). She found when there are multiple developers with different combinations of heterogeneous risk attitudes, their collective effects on spatial patterns are negligible. Due to the counteracting effects from different combinations of heterogeneity, the difference in the result is indiscernible.

5. Conclusion and discussion

This paper evaluates the effects of agent heterogeneity in an agent-based land market model. Three series of experiments are designed to explore how the introduction of agent heterogeneity, degree of agent heterogeneity, and collective effect of multiple sources of agent heterogeneity affect the model outcomes, in both spatial and socioeconomic dimensions. The results demonstrate that agent heterogeneity has considerable impacts on the spatial distribution of land use as well as socioeconomic outcomes. More specifically, we found the landscape metrics and socioeconomic outcomes between homogeneous and heterogeneous agents are significantly different, especially when more market mechanisms are incorporated. These results indicate the complex interactions between agent heterogeneity and market representation and the importance of agent heterogeneity in an ABLMM. In terms of the effects of agent heterogeneity, the two sources of agent heterogeneity examined in our experiments have different effects. Budget heterogeneity induces changes in transaction price and spatial fragmentation, and the increasing degree of budget heterogeneity will lead to a more heterogeneous distribution of transaction price. Preference heterogeneity, by contrast, is highly pertinent to spatial patterns, and the increasing degree of preference heterogeneity will encourage compact developments in the urban core but sprawling developments in the suburbs.

These findings imply that the relationships between agent heterogeneity and macro measures are not uniformly monotonic. And they indicate the importance of introducing an appropriate magnitude of agent heterogeneity in an empirical study. Our findings also suggest that differences in market representation are likely to be an important factor in reconciling some conflicting conclusions drawn by some other models. With regard to the collective effects from multiple sources of agent heterogeneity, our results show the difference among metrics depends on both the market representations and the interactions of agent heterogeneity. Further, the effects of the two sources of agent heterogeneity can counteract each other, which can potentially lead to some emergent results. It also suggests the ability of ABM to simulate emergent phenomena at the aggregated level from agent heterogeneity at the individual level.

One interesting and unanticipated point to emphasize is that the limitations of the models with less market representation are revealed only in the cases of heterogeneous agents. Taking a closer look at the results at market L0, the homogenous case shows a classic downward-sloping rent gradient as in the classic models of Von Thünen and Alonso. It, however, disappears with heterogeneous agents (see the first row of 3D bar charts in Fig. 8). Yet, in markets L0.5 and L2, in which competitive bidding is activated, the rent gradients and circular zones of land prices ranges appear again with and without budget constraints (see the second and the fourth rows in Fig. 8). It implies that competitive bidding is essential to reproduce the result of classical urban land market models in a spatial ABM, especially if agents are heterogeneous.

LUXE provides the opportunity to evaluate complex interactions in a land market due to its capability to encapsulate multiple sources of agent heterogeneity as well as its potential to offer broader kinds of outputs. To our knowledge, this is one of the first attempts to systematically explore the effects of agent heterogeneity in an ABLMM. Both landscape patterns and socioeconomic patterns are evaluated by different measures. The results enrich our understanding on the processes, which drive residential patterns, and give us more confidence in confirming the importance of agent heterogeneity and market representations.

There are also some inevitable limitations in this study. Currently, although the model simulates residential choice beyond the means of static economic equilibrium by introducing bilateral interactions between agents, the dynamics of immigration and emigration are not included. Additionally, the model is a relatively closed system since all the buyers are introduced into the model at initialization. Simulating the timing of buyers entering the model based on empirical data is a challenge, which we aim to address in the future. Similarly, the buyers are not allowed to relocate once they settle. The relocation process, such as affluent household moving to suburb due to the local neighborhood degradation, cannot be simulated in the current version. However, studies show the relocation process is also one of the main factors in shaping the urban landscape (Benenson, 1998; Dieleman, 2001; Ettema, 2011). Hence, simulating the relocation process is the next step to improve the model.

In addition, only two sources of agent heterogeneity (i.e. budget and preference heterogeneity) were examined in this paper. The rationale for choosing these two is that, intuitively, they are highly related to land market processes represented in LUXE (i.e. budget constraints and competitive bidding). However, additional sources of agent heterogeneity potentially play important roles in influencing land market outcomes, such as risk attitudes (Filatova et al., 2011; Ligmann-Zielinska, 2009), and ability to process knowledge (i.e., bounded rationality (Manson, 2006; Manson & Evans, 2007)). LUXE has a mechanism to incorporate bounded rationality by limiting the number of parcels that a buyer evaluates for bidding, in order to simulate incomplete market information. This mechanism is switched off in the current paper, in order to minimize random elements and provide a clean test of the effects of land markets and comparison to the benchmark analytical urban land market model. The next stage of model development will also incorporate risk attitudes and uncertainty.

Finally, the computational load of the model needs certain consideration. Under current landscape range (61 by 61 cells), adding land-market processes, especially the process of competitive bidding, greatly enhance the calculation burden of the model, because that, under this mechanism, every seller can receive up to 400 bids (equal to the number of buyers) and choose the highest. Failed buyers will re-enter the model and iteratively bid for parcels until no more transactions can be made. Therefore, adjustment of the model initialization (e.g., landscape size, number of buyers, number of parcels that a buyer evaluate for bidding, number of bids allowed for one parcel) and inclusion of additional processes (e.g., immigration, emigration, relocation, risk attitudes and bounded rationality) will inevitably increase the computation load of the model and may need more advanced programming technique (e.g., parallel computing) to increase the calculation efficiency (Parry & Bithell, 2012).[7]

[7] We scaled up the model and re-run it for 10 repetitive runs. Specifically, we increased the landscape size from 61 by 61 to 101 by 101 and the number of buyers from 400 to 600. The results show that, while there are some quantitative differences between the two sets of outputs, the qualitative patterns and conclusions of our analysis will hold.

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