The implications of land-market representation for the interpretation of empirical land-use change models

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1. Introduction

Economists, planners, and policy makers in related fields often seek to understand the determinants of urban land-use development patterns and their associated land values. They also seek to understand future trajectories of these factors. Economists often employ hedonic regression models for these purposes. On their own, such models reveal correlations between the built environment, its spatial structure, and the characteristics of market participants and market land values. By combining regression models with land-use change projection algorithms developed in other fields (Verburg et al. 2006; Plantinga and Lewis 2014), such models can also be used to project trajectories of land-use change and land value (Irwin and Bockstael 2002). In more recent work, hedonic regressions have also been used to form the basis of transition rules for representing market interactions and endogenous price formation in agent-based computational economic and microsimuation models (see (Huang et al. 2014) for a review). In either case, the resulting model projections are often used for policy, scenario, and impact analysis.

Hedonic models have proven useful in defining implicit prices of attributes for heterogeneous goods such as housing goods (Irwin 2002; Bin and Landry 2013). In theory, the transaction prices to which a hedonic model is applied represent a short-run equilibrium result derived at the intersection of the representative demand and supply curves for differentiated products (Rosen 1974). Yet, regression models offer only a reduced-form representation of the underlying structural determinants of decision-making in markets. In principle, a market transaction represents the result of bargaining between a buyer and a seller, each having their own willingness to pay or accept (WTP/WTA) and corresponding bid or ask price. However, if a regression model is estimated based on market transaction data, it reflects the net result of negotiation between buyers and sellers at a certain moment in time. As noted by Bockstael (Bockstael 1996) a hedonic model estimated as a snapshot of a market at one point based on spatial attributes in time may not capture underlying preferences of buyers or costs of sellers, and is not robust to changes in buyers preferences or incomes or in the supply of heterogeneous properties. Thus, in principle it is impossible to identify the individual WTPs of buyers and WTAs of sellers that underlie the equilibrium transaction price. This goes in line with Rosen's (Rosen 1974) statement that "estimated hedonic price-characteristics functions typically identify neither demand nor supply". Nevertheless, hedonic analysis based exclusively on spatial attributes of properties is often applied to land and housing markets.

In the best-case scenario however, a researcher might have access to information about buyers and/or sellers (referred to as "agent data" in this paper), in addition to data on the market property and its built form and locational attributes (the latter two are referred to as "spatial data" in this paper). In this case, a regression model could be used to estimate an upper or lower bound of WTP or WTA. However, in most current applications, hedonic models are estimated using only built form and locational attributes data (hence referred to as hedonic analysis based on "spatial data", HA_S). While often researchers are lucky to even access basic transaction data, the consequences of omitting agent data need to be considered. When characteristics and budgets of buyers and sellers are omitted, as demonstrated in our earlier work, HA_S models may suffer from omitted variable bias (Filatova et al. 2009b). This bias should in principle also affect land-use patterns and price projections based on HA_S models. However, this potential source of bias is yet unexplored.

Hedonic regression is applied to project change using a range of methods (Plantinga and Lewis 2014). The simplest of these sequentially selects locations and allocates them to their highest value or most suitable use, limiting the number of converted locations to a pre-determined number. More sophisticated methods allocate locations probabilistically, conducting Monte-Carlo style runs to create distributions of land-use change outcomes. At the higher end of the complexity spectrum, simulated markets are used to project change (Huang et al. 2014). When economists make change projections using regression models, they tend to follow the first or second approach, both of which omit important market mechanisms such as budget constraints and competitive bidding. As shown in recent work, in a theoretical context, this omission affects projected rates of change and patterns of land values (Huang et al. 2013; Sun et al. 2014). The implications of this omission when regression models are used have yet to be explored. Further, although allocation via a market mechanism seems a promising approach, its potential effectiveness has yet to be formally assessed. This paper will use an agent-based economic approach to study these two open questions.

Agent-based modeling (ABM) is a simulation methodology that is increasingly used throughout the social sciences (Berry et al. 2002; Edmonds et al. 2008; Waldrop

2009) and in economics in particular (Arthur 1999; Tesfatsion 2002; Farmer and Foley 2009). ABMs are computational simulation models that operate at the scale of real-world decision making and grow a macro-phenomena of interests (for example prices and trade volumes in economics) through direct representation of micro-economic decisions and interactions among economic agents. ABMs are increasingly being applied in an economic context, to address problems whose complexity renders them analytically intractable (Tesfatsion and Judd 2006). In contrast to mathematical or computational techniques traditionally used in economics, ABMs are simulation-based, not equilibrium-based. Although models may reach equilibrium, the equilibrium results from interactions among lower-level entities. ABMs can thus be used as computational laboratories to explore the path and equilibrium of an economy under different scenarios representing particular market structure, populations of actors, and sets of economic incentives and constraints (Tesfatsion 2006).

An active subfield in ABM is modeling land markets. These models combine representations of key buyer and seller actors, a spatial landscape, and a set of rules governing transitions. They produce a history of land-use change events and land transactions, from which measures of economic and spatial structure can be derived. Recent models are reviewed by (Parker and Filatova 2008; Irwin 2010; Schreinemachers et al. 2010; Huang et al. 2013; Parker 2014).

This paper uses an ABM of a land market (Land Use in eXurban Environments, or LUXE) to explore the potential real-world implications of using hedonic regression models to project land-use change patterns. Using the ABM framework as a virtual laboratory, we generate output data from a simulated land market where land is allocated through a budget-constrained competitive bidding process. We consider this as our "real-world data" baseline. We then apply standard statistical techniques used to analyze real world transaction data and to make price and spatial patterns projections.

We then estimate hedonic regression models based on these simulated land values. We first explore what would be the best case a researcher might face empirically—one where individual buyer data (with sellers assumed to be homogeneous) are available, creating the opportunity to estimate a theoretically unbiased hedonic model (HA_{AS}). We also estimate a similar regression using spatial data only, the more common real-world case. (HA_S).

We then use these regression results to conduct four experiments projecting project land-values and spatial patterns of, land-use change using a modified version of LUXE. For each hedonic regression (HA_S *and* HA_{AS}), we apply two projection algorithms. In each projection, the estimated hedonic model is used to represent the buyers' WTP for properties. The best-case scenario utilizes the LUXE model to allocate land through a simulated market. The second case uses a first-come first-served algorithm, which is equivalent to algorithms often used in practice for real-world land-use change projection. For all four experiments, we analyze the difference between the outcomes simulated using the hedonic WTP and the original "real-world" outcome, derived using a constrained utility maximization approach, comparing both land values and spatial patterns.

Data from these four experiments are used to explore the following research questions:

- How successfully can hedonic-regression-based projection algorithms be used to recreate the structure of urban landscapes, when used to project land-use and land-value change?
- How is the accuracy of the projection process affected by the degree of market representation used in the projection algorithm and the availability of actor-level data to parameterize the regression model?

The goal of our experiments is to bring a new perspective to methods currently used to estimate land values and project change. Specifically, this paper explores the potential added value of (1) obtaining buyer and seller data to supplement hedonic land value regressions, (2) using competitive bidding algorithms to project land-use change, given a set of estimated empirical WTP values, and (3) enriching statistical techniques applied in spatial economics by employing an ABM as a virtual laboratory to explore the impacts of omitting agent-level data in hedonic analysis.

The paper is structured as follows. Section 2 briefly reviews the structure and terminology of the LUXE model, and presents our experimental design. The simulation results and their methodological implications are discussed in Section 3. Section 4 offers summary conclusions and discusses limitations and next steps.

2. Methods

2.1 Agent-based land market model: LUXE

LUXE is a stylized ABM of urban land development, which was designed specifically to explore the implications of alternative representations of land-market factors on land-use modeling outcomes (Robinson et al. 2013). It differentiates among four key elements of land markets: preferences, budget constraints, competitive bidding, and endogenous relocation. The LUXE model implements several levels of market representation gradually building up the complexity. Level zero (L0) starts from land allocation driven only by location preferences of agents. An addition of budget constrains (L1) and competitive bidding (L2) allows the tracing of some key land market dynamics in a spatially heterogeneous landscape (Parker et al. 2012). This structure facilitates experiments that relate market levels to various model outcome metrics measuring the level, structure, and pattern of land-use change and land values. LUXE's assumptions and structure are designed to closely mirror analytical analogs such as the Alonso-Muth model under its Level 2 (L2) implementation. The L2 model is also equivalent to the ALMA model (Filatova et al. 2009a; Filatova et al. 2009b; Filatova et al. 2011).

The basic structure of LUXE, described in detail by Huang et al. (2013) and Sun et al. (2014), is illustrated in Figure 1 (Sun et al. 2014). LUXE is a bilateral land market model with sellers seeking to sell their land and buyers trying to acquire properties that maximize their utility. For the purpose of this paper we have implemented homogenous sellers, who all put their parcels on the market at a fixed price equal to the agricultural land price at initialization. In any model implementation, all buyers are initially active in the market. Buyers are sequentially active, and when active, they assess all parcels on the market, calculate their utility for each parcel and identify the parcel on the market that provides highest utility. In different implementations of market levels this process may be constrained by their budget (L1), and buyers may compete with other buyers for the same parcel (L2). When competitive bidding is present, the seller evaluates all the bids he has received, and selects the highest, if it is above his

WTA. If a buyer does not succeed in buying a property, she remains on the market and searches again in the next round. Unsuccessful sellers also remain on a market and wait for an interested buyer. A short-run equilibrium is reached when no more transactions occur. In the absence of a market (L0), this occurs when all buyers have acquired a property. In the presence of market mechanisms (L1 and L2), when all the gains from trade are exploited, some buyers typically do not find a parcel to purchase, which implies that quantity and location of land conversion is endogenous.

[Figure 1 about here]

Previous experiments with LUXE delivered the following key findings:

- As would be expected, the imposition of budget constraints and competitive bidding reduced the projected quantity of change. The primary effect moving from L0 to L2 came through the budget constraint, by preventing economically implausible transactions. However, a smaller effect occurred through buyer competition, as some buyers were unable to compete for their preferred parcels, and, in this open city model, could not compete for an alternative parcel for which their WTPs was higher than the seller's reservation price (Sun et al. 2014).
- When buyers are heterogeneous in some aspects, competitive bidding is essential in order to reveal the downward-sloping price gradient predicted by theory and empirical observation (Huang et al. 2013; Sun et al. 2014). This result implies that it is essential to represent both actor heterogeneity and the process of competitive bidding, if estimates of the value of distance are sought from a model.
- In terms of spatial pattern, on average, higher levels of market representation reduced measures of model spread, although particular parameter combinations

showed different outcomes (Figure 2, (Sun et al. 2014)). Measures of fragmentation, however, increased, attributed to lower infill rates and better market sorting for preferred open-space amenities. However, landscape measures that controlled for quantity differences showed that the full market model projected less sprawling patterns (Sun et al. 2014).

[Figure 2 about here]

- In terms of effect of heterogeneous agent characteristics, preference heterogeneity for open-space amenities tends to lead to more compact close-in landscapes but more dispersed suburban landscapes, as agents with preference for proximity sort themselves to central areas. Budget heterogeneity affects socio-economic measures, leading in particular to higher land rents when markets are fully implemented. Differences due to increased heterogeneity are magnified as the degree of market representation increases (Huang et al. 2013).

2.2 Experimental Design

To answer our two research questions several experiments are conducted following the flow chart in Figure 3.

[Figure 3 about here]

In the first step (top right box), the *original* LUXE model is used to conduct multiple runs, following the same methods described in Huang et al. (2013) and Sun et al. (2014), using its original utility function based on a Cobb-Douglas form and *WTP* function:

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

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

where U stands for utility; A is the measure of open space amenity; and P stands for the proximity to the CBD, which is a standardized measure of the distance to the CBD (D). Both A and P range from 0 to 1; α and β are the weights for A and P respectively, and $\alpha + \beta = 1$; WTP denotes the buyer's bid price in this simple model implementation; B stands for the individual budget, and $t \cdot D$ is the transport cost to the CBD, with t being the transport cost per unit of distance; b is a constant that represents the affordability of all non-housing goods. The output from these model runs, for the purpose of our four computational laboratory experiments, is considered to represent "real-world" transaction prices and land-use patterns.

In the second step (bottom right box in Figure 3), we estimate hedonic regressions, using the transaction results of the original "real-world" model as their dependent variable, producing the estimated WTP (WTP_S and WTP_AS) functions. For WTP_S and WTP_AS , regression functions were as follows respectively:

$$WTP\_S = a_1 + b_1 \times D + c_1 \times A \tag{3}$$

$$WTP\_AS = a_2 + b_2 \times D + c_2 \times A + d_2 \times B + e_2 \times PR \tag{4}$$

where WTP_S denotes the estimated WTP based on the spatial data only, which are the distance to the CBD (D) and the open space amenity (A) respectively; WTP_AS stands for the estimated WTP based on the spatial data and the agent data, which also include the budget (B) and the preference for proximity (β); and a_1, b_1, c_1, a_2, b_2, c_2, d_2, and e_2 stand for the estimated coefficients from regressions.

In the third step (bottom of left box in Figure 3) , we replace the original WTP and utility functions with the hedonic equations generated above. Note, that this replacement represents a change in model structure on two occasions. First, the analytical utility function used for ranking parcels to bid on is replaced with the simulated money-metric utility— i.e. equation 3 or 4 replaces equation 1. Second, the hedonic WTP function replaces the analytical WTP function— i.e. equation 3 or 4 replaces equation 2. The modified models were used to conduct multiple runs (each experiment was run 30 times with different random seeds) and to generate corresponding "simulated" transaction prices and land-use patterns. For each stochastic seed used to generate the original model, the corresponding regression model is used. The same stochastic seed is then used for the land-use change projection experiments. This implies that the generated population of buyers will be identical for each paired experiment.

In the fourth step (left panel), comparisons of transaction prices and land-use patterns between the original model (utility driven by Cobb-Douglas Utility functions) and the simulated models (utility driven by hedonic land value regressions) are made to explore how effectively hedonic regression functions could be used to project land-use and land-value change.

As described in Table 1, this paper presents five experiments under market levels L0 0 and L2 .There is no competitive bidding or budget constraints in market level L0, which leads to the sequential allocation of parcels agent-by-agent based on the first-come, first-served rule. In the market level L2 experiments both competitive bidding and budget constraints are present. In each case (L0 and L2), simulated land-use change projections are done using either spatial data only or spatial-plus-agent regressions. Therefore, five experiments are conducted: Original model; L0_WTP_S; L0_WTP_AS; L2_ WTP_S; L2_ WTP_AS.

[Table 1 about here]

As described in Table 2, constant parameters and market-level parameters representing agents' characteristics, the economic environment and the spatial environment are used to perform all experiments in the models.

[Table 2 about here]

3. Results

3.1 Hedonic analysis

Results of two linear hedonic regressions applied to the data from the original model are shown in Table 4. In the HA_S model (WTP_S from Equation 3) independent variables (D-distance to the center, A-open space amenity level) represent spatial heterogeneity. In the HA_{AS} model (WTP_AS) from Equation 4) independent variables (D, A, B-individual budget, PR/ β -preference to proximity) represent both spatial and agents' heterogeneity. In each case, the realized transaction price is the dependent variable. Conceptually these regressions are similar to those presented in (Filatova et al. 2009a; Filatova et al. 2009b; Filatova et al. 2011). Consistent with previous work, the spatial only regressions show evidence of omitted variable bias, as expected. As shown in table 4, the influence of distance parameter, represented by the *b* coefficients, is uniformly higher in the spatial-only model, as is the open-space amenity value (represented by the *c* coefficients). The model goodness-of-fit is also uniformly lower in the HA_S case. The take-home message is that, while the use of hedonic regression based on only spatial variables is a practical compromise that many researchers must make, there is a potential cost to that compromise in terms of reduced model accuracy due to missing variables.

Part of the goal of this paper is to assess what practical difference this compromise makes when the hedonic models are used to project land-use change.

[Figure 4 about here]

[Figure 5 about here]

[Table 4 about here]

3.2 Land-use change and transaction prices patterns

A graphical exploration of land-use and transaction price patterns is shown in Figures 4 and 5. Figure 4 compares the original model to the outcomes of land-use change projections using the L2 model—the one that uses market mechanisms to project change. These two cases represent what we consider to be the best current method to project land use change. Our expectation is that L2_WTP_AS should be our best case, with L2_WTP_S falling somewhat behind due to the omitted variable bias.

[Table 5 about here]

In the original model, clear relationships are seen between transaction prices and distance (negative) and budget (positive). These patterns are strongly qualitatively mirrored in L2_WTP_AS, indicating initially that the experiment reasonably replicates relationships in the original landscape. However, although L2_WTP_S effectively replicates the value of distance and open-space amenities, the output transaction values do not reflect the increasing budget purchase power (Figure 4f). On the one hand, this may appear surprising given that agents are operating under budget constraints. On the other hand, it is understandable as buyers' market valuations and bids don't reflect their differential buying power in L2_WTP_S, in contrast to L2_WTP_AS, (Figure 4b).

Moving on to the level 0 models (Figure 5), we explore the results of land allocation via the first-come-first-served maximum utility rule, which lacks both a budget constraint and competitive bidding. As expected, this algorithm does not perform as well as the market algorithm, even when the agent-level variables are included. However, L0_WTP_S still reveals a downward sloping rent gradient related to the value of reduced transport costs from proximity. This result may initially seem surprising since our previous work with the LUXE model showed that when agent heterogeneity is present, the L0 model failed to reveal a downward-sloping price gradient. The downward-sloping price gradient seen here can be explained by two factors. First, since agent-level characteristics are supprsed in the regression equations, heterogenous buyers are essentially represented as homogeneous in the estimated WTP functions, as their differential agent characteristics are not expressed through independent variables. Second, as seen in the regression output, the estimated value of distance is magnified due to omitted variable bias. Thus, the projections reveal a downward sloping rent gradient, even in the absence of competitive bidding. As expected, no relationship is seen between budget and price. Open-space amenities remain fairly robustly represented. This success may be due to the fact that, given the Cobb-Douglass utility specification of the original model, buyers face a tradeoff between amenities and proximity, and proximity is highly correlated with transportation costs. Thus, open-space amenities values, also correlated with a spatial variable reflecting their level, are picked up by that spatial variable. The result may not be robust in a case where buyers had highly variable and non-monotonic preferences for open-space amenities.

Moving on to the L0_WTP_AS outcome, the rent gradient is now much more weakly represented. This result is consistent with the previous LUXE results, however, and can be explained by the lack of competitive bidding when buyers are heterogeneous. Interestingly, although the budget constraint is not binding, a strong relationship is seen between budget and price, reflecting the presence of the budget as an independent variable in the regression model. (Note that in the original LUXE model, the budget constraint served mainly to cut off economically implausible transactions, where the buyer's WTP was below the seller's reservation price.)

3.3 Spatio-temporal patterns of land rents

Figures 6 and 7 further explore patterns of land rents. The 3-D plots show the height of the transaction price, with color coding for the transaction time. They show that the market algorithm sequentially allocates land from the city center (initially most valuable as it is high in both proximity and amenities) outwards, with land transaction prices falling over time. The figures show that, as expected, the L2 models both reasonably replicate the pattern and timing of land transactions. In contrast, the L0 models project faster land transitions in the absence of competition, with the L0_WTP_AS model failing to reveal the downward-sloping land rent gradient.

[Figure 6 about here]

[Figure 7 about here]

Figures 8 and 9 show a top-down view of land transactions and prices, which more clearly reveal commonalities in land-use pattern.

[Figure 8 about here]

[Figure 9 about here]

These figures are supplemented in Table 5 by formal average measures of pattern between experiments. Table 5 compares values of selected quantity and pattern output metrics, showing their statistical significance relative to the average "original model" baseline. Figure 10 provides a graphical summary of differences between experiments. Sun et al. (Sun et al. 2014) break measures of land-use pattern down into several aspects for the purpose of comparison: spread, fragmentation, and quantity-controlled sprawl. In this paper, we report metrics that reflect the first and third aspects. Average transportation cost $\bar{C}_{tran}$ reflects overall spread. Metrics ρ_e^q, AI^q, LSI^q, and CI^q reflect patterns of sprawl, adjusted for differing numbers of converted cells between model runs. While ρ_e^q is positively correlated with patterns that would be viewed as fragmented, the other three measures are negatively correlated.

[Table 5 about here]

[Figure 10 about here]

3.4 Quantity of change

As discussed in Sun et al. (Sun et al. 2014), the quantity of land-use change is essentially endogenous in the L2 models, which are open city models, but exogenous in L0 models, where each buyer agent acquires a parcel. Consistent with this, the quantity of change is much higher in the L0 experiments. Consistent with common practice, however (Verburg et al. 2006; Plantinga and Lewis 2014), these quantities could be reconciled by constraining the number of agents to that in the original model. Notably, however, the average quantity of change in the L2 experiments is quite close to the original model, which encouragingly indicates that market mechanisms based on hedonic regression might project quantity of change reasonably well. That said, both quantities of change are significantly different from the original model. (Note that since we are doing essentially population-level analysis, some computational modelers reject the concept of using statistical significance to assess differences between model runs. However, as we are comparing models with different rules and structure, we argue that the the use of significance levels is valid in this context.)

3.5 Economic Metrics

Mean transport cost (spread) Consistent with the higher quantities of change, the mean transport cost in the L0 experiments is higher than the L2 ones. Again, although the L2 outcomes are significantly different, they are in the same range as the original outcome.

Transaction prices Since reservation prices and budget constraints are not binding in the L0 models, the minimum transaction prices fall below those seen in the original model, skewing average values downward. Maximum prices show less range. However, as expected, L2_WTP_AS shows the strongest match to the original model, as budgets are reflected in valuation, and competition allocates parcels to the buyer with the highest value. These measures are significantly different at only a 10% level.

3.6 Measures of fragmentation

Measures of fragmentation show that the L2 experiments produce more compact and less fragmented landscapes than the L0 models. (Note that this result could be a function of the particular parameter settings used in this model, in particular the assumptions about preferences for open space and proximity.) As shown in Table 5, again L2_WTP_AS comes closest in term of replicating the fragmentation patterns of the original model, with outcomes being statistically significantly different at only a 10% level.

4.Conclusions and discussions

In this paper, we have presented a thought experiment using an agent-based land market model as a computational laboratory, in order to theoretically explore how effectively hedonic regression can be used to form the basis for land-use and land-value change projection algorithm. Working from the assumption that the output from a utility-based, budget constrained land market model represents a set of "real world" transactions, we estimated hedonic regressions, one incorporating and one leaving out buyer characteristics. We then compared the effectiveness of two alternative land-use change projection algorithms. The first used a very similar market mechanism to the "original" model to project land-use change, endogenously determining the quantity of change. The second used a "first-come-first-serve" algorithm that sequentially allowed each buyer agent to select their highest-value parcel. The second algorithm more closely resembles algorithms commonly used to project land-use change for both regression and cellular automaton models, in which cells or parcels are sequentially allocated to their highest-valued use.

We find, as we hypothesized, that on the whole, the market allocation most effectively replicates the pattern and quantity of land values and land transitions in the original model. Although not providing a statistically significant match, the market model that utilizes buyer level data provides qualitatively similar results and quantities that are within reasonable range of the original model. These results imply that, if data are available on the characteristics of market participants, hedonic regression combined with a market allocation mechanism can be used with a reasonable degree of confidence for land-use change projection. When buyer characteristics were not included, the model still effectively replicated land-use patterns, but fell short in projecting the relationship between buyer budgets and land values. The lesson here is simple—if we lack data on important agent-level drivers, our regression estimates will not reflect these drivers, and this deficit will spill over into our land-use change projections. Policy analysis should thus be cautious in interpreting the resulting projections.

Results using first-come first-served projections are mixed. In contrast to the results from analytical simulation models, using a spatial-only regression, the value of distance is still revealed, as the influences come through to some extent through the regression coefficients, which reflect the net effects of both transport cost and preference for proximity. However, similar to the WTP_L2_S case, land values don't reflect agents buying power or other sources of agent heterogeneity. Using the spatial and agent characteristic regression, budget values are revealed, as would be expected since these are reflected in WTP. However, land transaction prices do not reflect the value of proximity, or the interplay between budget and proximity that is an essential feature of sorting through land markets. The implication of this set of experiments is that first-come first-served allocation algorithms should be used with caution, especially when policy makers are interested in projecting land value patterns.

There are several directions for future work, which are worth pursuing. Firstly, we are in the process of testing two additional analysis methods for a comparison of the landscapes. The first will utilize traditional location-based map comparison algorithms to assess each experiment's ability to replicate the location and quantity of change. The second will use additional regression analysis to test how well each experiment can replicate the original regression coefficients associated with the original landscape.

Second, one could perform additional analysis of the macro metrics. This paper has used a variety of methods to analyze differences between experiments. Most, however, are based on graphical and descriptive statistical analysis based on averages. Further, we report results from a single set of parameters, which would represent a particular market context. Future work will run the same set of experiments for multiple parameters settings. We can then use alternative methods to explore differences between particular parameterizations, as well as look for generalities across parameter sets, following (Sun et al. 2014)

Third, Parker et al. (2012) identify endogenous relocation as an important element in land-market models, and (Huang et al. 2014) review many ABMs that contain this feature. Yet, it is not included in the LUXE model. This omission likely affects final patterns of land values, as there should in principle be a fall in the value of closer-in properties as infill occurs and open-space amenity values are reduced. While successor models to LUXE contain endogenous relocation, they also contain additional complexity such as developer agents. Assessing the robustness of this paper's conclusions when endogenous relocation is added is an important next step.

Moreover, in order to generalize our results, in future we plan to evaluate two additional land-use change projection algorithms. For the first, rather than selecting buyers sequentially and letting each choose their highest valued parcel, we will select parcel by parcel (using a random allocation algorithm), identify the agent with the highest value, and allocate the parcel to that agent. This projection method will more closely resemble that most commonly used for land-use change projection. We expect this method may change projected patterns, as well as the temporal sequence of development from city center. Second, in data-sparse situations, researchers are often only able to estimate limited dependent variable models of binary land-use change events. Using our original landscape, we plan to categorize parcels into "converted" or not, and then apply logistic regression models to estimate a probability of change, incorporating spatial neighborhood relationships. Then, Monte-Carlo methods (per Plantinga and Lewis, (2014)) will be used to project land-use change. This analysis will provide additional insight on the potential effectiveness of using regression models for projecting land-use change.

Finally, our methods could be applied to a real-world landscape, in order to compare the relative performance of each regression methods and projection algorithm, if needed data were available. In principle, the researchers would need data on both buyer and seller characteristics, as well as spatial attributes, property characteristics, and transaction values. Our long-run research goal is to develop such a model, provided we are able to obtain the needed data.

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