Incorporating Urban Spatial Structure in Agent-Based Urban Simulations

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Introduction

In recent decades, increasingly sophisticated models have been proposed to understand the complex and interdependent social and physical factors involved in the development of sustainable urban systems. A recent OECD (Organization for Economic Co-operation and Development) report points out that, despite recent advances in computational capacities, methodological difficulties still prevent the development of efficient and user-friendly urban modeling tools [1]. This gives a fair overview of our current status on urban system research. The challenges we face in modeling urban systems become more and more structural as we keep improving computation technology. Over the second half of the twentieth century, the research approach on urban systems has gradually transformed from traditionally physical design-focused to a framework with more attention on social and economic processes (e.g. [2–5]). The transition features at least three new standing pillars of urban modeling: behavior component, spatial interaction, system dynamics. Incorporating these modeling aspects into urban system models calls for a more integrated structural understanding of urban systems. Such a structural understanding of urban systems is not only necessary to the management of city operations, but also fundamental to public policy-making. It requires modeling of urban systems to take into account all physical/geographic, social, economic components, and their interrelationships in a simplified but informative way.

To understand the structure of urban systems, a starting point is the behavioral motivation of the city: why do people live in cities? Gutkind [6] answers the question as following: an unfulfilled longing for the amenities and distractions of city life

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has driven people living in cities, where men have developed more differentiated habits and needs within proximity. Recently, Glaeser [7] answers the question with more enthusiasm: people come to cities in search for something better. Cities are proximity, density, and closeness at a much larger scale. The human nature of desire for connections and proximity, searching for more and better choices, has driven people to work and live in cities. How this human nature is organized into a landscape where different people, culture, and sectors are integrated is the key to understand the structure of urban systems. It is easy to understand why the rich and the middle-class choose to live in the cities and bear higher living cost, for example, but why the poor? One observation is that, the urbanization of poverty may be explained by the better access to public transportation in cities [8]. In a nutshell, it is the diversified preferences that drive urban residents' choices, and the urban system exists as an aggregate representation of all individual choices.

From a modeling perspective, the difficulty also lies in between calibrating household behavior and aggregate representation. The complexity in understanding household behavior comes from the fact that urban residents face an even larger choice set, while that is also what is fascinating about cities. Location choice is the major decision of each household in the city, because many of the amenities and distractions of city life are likely associated with location. Location is also the basic component of any urban systems. All developed locations and open space left in between constitute a continuum of urban landscape, which is the framework urban systems build upon.

Given location choices and income constraints, households decide on the amount of consumption through a series of decision making mechanisms. The current simulation approach to urban systems seeks to link together different sub-systems and markets through modular architecture with substantial geographical details and level of behavioral realism (e.g. [9, 10]). The advantage of such approach is that it is good at simulating short run evolution of urban systems at an extremely disaggregate level. The disadvantage, on the other hand, is that such multi-agent system is vulnerable to structure change, especially in the long run. In other words, current urban simulation models tend to perform well in descriptive explanation, but lack strong ability of prediction (e.g. in land use change and ecosystem applications). In today's regional economy, not only is the gradual-adjustment type of public policy process important, but also the public policy for long term regional development planning. To address both types of policy needs, it is critical to develop urban simulation tools which are robust to structure change and capable of predicting urban evolution in relatively long run.

In this chapter, we focus on the role of urban spatial structure in urban simulations, and how it helps to strengthen the current simulation approach to urban systems. As discussed in Crooks et al. [11], one of the key challenges to ABM simulation in geocomputation is to what extent the model is rooted in independent theory. Basing on household behavior, urban spatial structure theory integrates economy system, land use, and transportation system together, which provides an easy to implement framework for simulating urban systems. Methodologically, urban spatial structure theory also provides a trackable way to measure performance and efficiency of urban systems, which is valuable to public policy-making. Section "Components of Agent-Based Urban Simulation" discusses basic components of agent-based urban simulation. In sections "Incorporating Urban Spatial Structure", "Transportation and Congestion: An Application", and "ABM Simulation: Land Development and Congestion," a monocentric city simulation model of transportation cost and congestion effects is developed to illustrate how urban spatial structure models can be integrated with ABM simulation. Section "Concluding Remarks" concludes the chapter with discussion on policy implications and future research.

Components of Agent-Based Urban Simulation

Urban simulation models are constructed to address operational needs in planning and policy-making for increasingly complex urban systems. Many well-known urban simulation models have two basic functionalities: land use and transportation. From a modeling perspective, an agent-based simulated urban system should have three categories of building components: households, spatial interaction, and landscape. In this section, we discuss the role of each category in urban simulation. These components are also essential constituents of urban spatial structure models.

Household Behavior

The human behavioral component is the building block of many observed social and economic phenomenon. The first basic behavioral component of a urban system is household—each household acts as a node in the network of urban systems. The decision and choice made by one household can directly or indirectly affect the behavior of other households across the city. In the economics approach, the (rational) behavior of a household is usually summarized into a mathematical form—utility function. The utility function approach provides a simplified way to represent the inter-relationship among all available choices. In the context of urban modeling, these choices are usually being categorized into housing consumption, non-housing consumption, and transportation consumption. Given household income as a binding constraint, the balance among three consumption categories can be realized through household location choice. Thus, optimal location choice is equivalent to utility maximization for a rational household.

Household behavior can be generalized to all sorts of agents—business owner, land developer, social planner, and etc. Similarly, the utility function can also be generalized to generic objective function—profit function, social welfare function, and etc. To completely describe the behavior of these agents, a decision making mechanism has to be established basing on the objective function. In most of mathematical social science fields, optimization theory is employed to develop decision making mechanism for agents. The idea is to maximize (or minimize) the objective by optimizing the combination of all available choices. Note that, for many of the urban system problems, a socially optimal decision is not necessarily optimal to all agents because of the resource constraints. On the other hand, if all agents make individual optimal decisions, the aggregate social outcome is also not necessarily optimal to the society (e.g. [12]). Such inconsistency between aggregate modeling and aggregated individual modeling has been a major challenge to analytical approach to urban systems. The advantage of agent-based simulation approach to urban systems, however, is to explore the aggregate social outcome (i.e. emerging properties) from a disaggregate level which the analytical equilibrium approach often fails to do [13].

Spatial Interaction

Individual households as agents are not isolated from each other. Urban households live within very close proximity, thus mutual interactions are an indispensable part of urban life. Households interact with each other through two important mechanisms: social network and market. Many systems take the form of networks, and all non-economic and some economic components of urban systems are connected through social networks. An important property of social network is the so-called small world effect or neighborhood effect, which means the network effects tend to be localized [14]. In urban spatial context, many of the spillover effects are associated with social networks, which is something to take into account in urban modeling and public policy-making. Bramoullé and Kranton [15], for example, show that individuals who have active social neighbors have high benefits from public goods with only little effort. The social network effects can influence household location choice, even though other factors are also important. Ettema et al. [16] suggest that social interactions between households and between individuals potentially have an influence on household location, mobility and activity choices. Wang [17] shows that neighborhood spillover effects through housing markets can affect the whole land development process in an urban area.

The connection through markets is more measurable, at least from the economic perspective. Households may compete with each other on the market—for instance, the labor market, where over-supply is often the case. Households may also corporate with each other through the market—for instance, form a labor union or business alliance, so that everyone can benefit from collective bargaining. In ABM simulation, a common approach of modeling market mechanism is to allow trade between agents [18]. Trade between agents is more like an atomic market, which is quite different from the macro market that all households can potentially participate. Coordination between atomic markets like trade mechanism and the macro market still remains a challenge to ABM simulation. In urban simulation, how to integrate different macro markets (e.g., housing market and labor market) into one simulation framework is a more pressing challenge, because to inform policy-making an understanding of the linkage among different markets is critical.

In short, because of the existence of social networks and markets, the aggregate social outcome in urban systems is no longer a simple adding-up of individual decisions. An urban simulation model which fails to consider the consequence of these interaction mechanisms may produce biased results.

Landscape

Landscape is the physical foundation of urban simulation. All scientific modeling requires some level of abstraction or simplification of reality and observed phenomenon. In urban modeling, the spatial configuration of agent activities matters. The conceptualization of urban landscape varies across different disciplines. For example, ecologists pay more attention on the structure of impervious surface and its impacts on ecosystem processes (e.g. [19]). Economists are more interested in the residential pattern and the spatial distribution of economic activities (e.g. [20]). These alternative perspectives on urban landscape are not independent from each other as they seem to be. The structure of impervious surface, for instance, is just a physical description of road system and residential development.

Landscape can be generated from image or GIS data of original urban layout using visualization techniques [21]. This approach is often used in scenario-based case studies. Another approach is to design landscape geometrically following certain pattern of urban configuration, and the transportation system is usually integrated as part of landscape. In a two-dimension urban simulation, landscape can be modeled in grid or circular form. Circular form is usually used to model monocentric urban structure, where each ring can be defined as a model unit. Grid form is more generalized, and it can be used in both monocentric and non-monocentric urban modeling. The smaller the circular rings and grid cells, the more realistic is the simulation. However, there is always a trade-off between computation time and level of details in time, space, and agents that a simulation model can represent. In practice, the choice of landscape form depends on the purpose of simulation and computation power available.

Incorporating Urban Spatial Structure

In this chapter, an ABM simulation on transportation cost and congestion effects is developed to illustrate the role of urban spatial structure in agent-based urban simulation. Due to space limit, the model is confined to the monocentric city model only. Different components of the simulation model will be discussed. The theory of urban spatial structure has inspired many analytical and empirical insights about urban systems, which should be integrated in urban simulations [11]. In general, analytical models like urban spatial structure models provide more tractable step-by-step procedures for simulation than heuristic models do.

The simulation framework is designed based on an urban spatial structure model which integrates household behavior, market interactions, and urban landscape. The idea is to illustrate how we can learn more about urban system dynamics through emergent properties by incorporating urban spatial structure with the ABM simulation approach. The basic setup for the urban spatial structure is following. The city consists of a continuum of households, living across the urban area. The homogeneous urban land is divided into many areas (residential and non-residential), not necessarily equally, each of which has fixed boundary. Households within each region have three major consumption categories: housing/land (residential, industrial, commercial, and etc.), non-housing, and transportation. In the model, we focus on transportation and congestion effects.

Transportation and Congestion[1]: An Application

The interaction between residential land use and transportation land use, which may be generalized to the interaction between land use and infrastructure, can result in potential negative externalities. Among which, congestion is the biggest concern in urban development policy. As Wheaton [22] points out, if urban land is allocated to the highest paying use (e.g. as in the Herbert-Stevens model [23]), aggregated land rent is maximized only if there is no externalities. In many of the conventional urban development models, especially spatial equilibrium models, transportation cost is given exogenously and with no congestion effects. In part, this is because congestion cost depends directly on the choice of travel/commuting routes. Modeling travel pattern even with low degree of realism poses challenges to the framework of spatial equilibrium models. On a two-dimension plane, roads and streets can go any direction, modeling travel pattern and congestion essentially becomes a high-dimension problem. Therefore, in either analytical modeling or simulation modeling, certain simplifications have to be made upon the structure of travel patterns. The advantage of simulation approach is that, it allows more details and flexibility in model implementation. In this section, an analytical urban spatial structure model with congestion is introduced, which can be solved as a closed-city optimal control problem. Basing on the analytical model, a dynamic simulation is designed to illustrate how urban simulation can be used to inform policy-making.

[1]Following Solow [27], congestion cost is defined as the cost of travel per person per mile at any point, which depends on two factors: the number of travelers using that part of the transportation system, and the amount of land allocated to transportation use at that point

Static Approach with a Closed-City

Given a circular monocentric city where N consumers commute inwards either to the central business district (CBD, the central labor market), or another region (the local labor market) between home and the CBD. The commuting distance (t),[2] if ignoring the local labor market, can be measured by the ray from the CBD to home. The city is a closed environment, with border at distance B. Following Solow [24] and Wheaton [22], an intermediate variable is created to reflect the potential travel demand, $n(t)$, equal to the number of households residing beyond distance t. In Solow [24] and Wheaton [22], this variable represents the number of commuters passing region t on their way to work in the CBD.[3] In this chapter's framework, residents may choose to work locally, thus the actual travel demand in region t can be less than $n(t)$. Intuitively, the marginal cost of travel in region t is expected to be a positive function of travel demand, and a negative function of transportation capacity in region t.

Travel demand and transportation capacity in region t can be defined as following. Let s denotes a region between region t and the CBD, i.e., $0 \leq s \leq t$, and $\alpha_{t,s}$ be the proportion of residents who live in region t and choose to work in region s. Assuming that all regions are discrete, and $s = 0$ represents the CBD region, then by definition $\sum_{s=0}^{t} \alpha_{t,s} = 1$.[4] The travel demand at region s, $D(s)$, can be expressed as:

$$D(s) = \sum_{i=0}^{s} \sum_{t=i}^{B-1} \left(n(t) - n\left(t+1\right)\right) \alpha_{t,i} \tag{1}$$

If all residents choose to work either in their residing region t, or in the CBD region, then the travel demand can be simplified to:

$$D(t) = \sum_{j=t}^{B-1} \left(n(j) - n\left(j+1\right)\right) \alpha_{j,0} \tag{2}$$

In continuous case, $D(t)$ can be written as:

$$D(t) = -\int_{t}^{B} n'(z) \alpha_z dz \tag{3}$$

where α_z is the proportion of residents who live in region z and choose to work in the CBD region, which can be a constant or a function of distance z.

[2]In this chapter, t is used as a discrete integer to denote both commuting distance and regions to simplify notation. This implies that all regions have the same width, but different areas

[3]For convenience, in the circular monocentric city model the distance to the CBD, t, is often being used to index land use region as well. In this case, a land use region is a ring around the CBD

[4]An implicit assumption here is that, residents living in region t do not choose to work in regions beyond t. Residents who work in regions beyond t are better off by choosing to live in their working region, because the congestion cost increases as it gets closer to the CBD

An implicit boundary condition here is $n(B) = 0$, due to the closed-city assumption. Transportation capacity is denoted as the fraction of the land allocated to roads and streets in region t, $\nu(t)$. Following Wheaton [22], the urban land development planning can be formulated as an optimal control problem, in continuous case:

$$\begin{cases} \underset{X(t),Q(t)B}{Max} & \int_0^B \left[\frac{Y-T(t)-X(t)}{Q(t)}\right] 2\pi t\,(1-\nu(t))\,dt + \left[A-\pi B^2\right] \\ & R_a+\beta\,[U\,(X,Q)-U_0] \\ \text{Subject to :} & T'(t) = c\left(\frac{D(t)}{2\pi t\nu(t)}\right) \\ & n'(t) = -\frac{2\pi t(1-\nu(t))}{Q(t)} \end{cases} \tag{4}$$

with two boundary conditions:

$$\begin{cases} T(0) = 0 \\ n(B) = 0 \end{cases} \tag{5}$$

Y, $T(t)$, $X(t)$, and $Q(t)$ are household income, transportation cost, non-land consumption (the numeraire, price is standardized to 1), and land consumption, respectively. A is the total land area available, and R_a is the opportunity rent of urban land (e.g. agricultural land rent). $U(X,Q)$ is the household utility function. $c(\cdot)$ is the marginal transportation cost, which is a function of the ratio of travel demand to transportation capacity $\frac{D(t)}{2\pi t\nu(t)}$. $c^{'}(\cdot)$ and $c''(\cdot)$ are usually assumed to be positive (e.g. [25]). The maximization problem in Eq. (4) can be solved following optimal control theory (see [22]).

Dynamic Approach with an Open-City

The static approach to urban land development planning in Eq. (4) ignores the urban evolution process. In reality, the urban evolution proceeds as a gradual process and takes decades to adjust [26]. Instead, the urban authority can choose to plan development stage by stage, i.e., planning and developing one region each time period rather than the whole urban area at once. The gradual development process, in many important aspects, is in analogy to the concept of regional economic evolution. At different stages of development, changes of economic and institutional environment can lead to updated perspective and goal on urban development planning. Therefore, a dynamic disequilibrium approach provides a better way to frame the planning problem, which is also one of the main advantages of simulation approach to urban modeling [10].

In the circular monocentric city, the development process goes naturally from the CBD to outside suburban area ring by ring. The land use and economic landscape may show path dependence, but new development can be treated as another planning problem conditional on previous development. Without loss of generality, index each ring region by natural numbers ($t = 1, 2, 3, \ldots$, with the CBD being region 0), and for any region t the optimization problem becomes:

$$\underset{X(t),Q(t)}{Max} \left[\frac{Y - T(t) - X(t)}{Q(t)} \right] 2\pi t\,(1 - \nu(t)) + \beta\,[U\,(X, Q) - U_0] \tag{6}$$

If t represents the newly developed edge region, then the change of transportation cost ΔT only depends on the travel demand originated from region t and the transportation capacity of region t. From the first constraint in Eq. (4), given that the distance horizon is discrete (and $\Delta t = 1$), we have:

$$\Delta T = T(t) - T\,(t-1) \approx T'(t)\Delta t = T'(t) = c\left(\frac{n(t)\alpha_t}{2\pi t\nu(t)}\right) \tag{7}$$

However, the transportation cost $T(t)$ (not $\Delta T(t)$) is not solely determined by conditions in region t, instead it shows path dependence:

$$T(t) \approx T\,(t-1) + c\left(\frac{n(t)\alpha_t}{2\pi t\nu(t)}\right) \tag{8}$$

By the recurrence relation, with boundary conditions $T(0) = 0$ and $n(t+1) = 0$, Eq. (8) can be written as:

$$\begin{aligned} T(t) &\approx c\left(\frac{n(t)\alpha_t}{2\pi t\nu(t)}\right) + c\left(\frac{n(t)\alpha_t + [n\,(t-1) - n(t)]\,\alpha_{t-1}}{2\pi\,(t-1)\,\nu\,(t-1)}\right) + \ldots \\ &= \sum_{i=1}^{t} c\left(\frac{\sum_{s=i}^{t} [n(s) - n\,(s+1)]\,\alpha_s}{2\pi i\nu(i)}\right) \end{aligned}$$

Following Solow [27], choose an exponential form for $c(\cdot)$, $c\left(\frac{n(t)\alpha_t}{2\pi t\nu(t)}\right) = k\left(\frac{n(t)\alpha_t}{2\pi t\nu(t)}\right)^m$, thus

$$T(t) \approx \sum_{i=1}^{t} k\left(\frac{\sum_{s=i}^{t} [n(s) - n\,(s+1)]\,\alpha_s}{2\pi i\nu(i)}\right)^m \tag{9}$$

where k and m are positive constant parameters. Note that, if α_s is constant for all regions, i.e., $\alpha_s = \alpha$, then $\sum_{s=i}^{t} [n(s) - n\,(s+1)]\,\alpha_s = n(i)\alpha$. $n(i)$ is the population residing beyond distance i, and $n(i)\alpha$ is the portion of that population who work in the CBD region. In this case, Eq. (9) can be simplified into:

$$T(t) \approx \sum_{i=1}^{t} k\left(\frac{n(i)\alpha}{2\pi i\nu(i)}\right)^m \tag{10}$$

Given transportation cost $T(t)$ computed according to either Eq. (9) or Eq. (10), and other parameters, the optimization problem in Eq. (6) can be solved from the following first order necessary conditions:

$$\begin{cases} \frac{U_Q}{U_X} = \frac{Y-T(t)-X(t)}{Q(t)} \\ U_0 = U\left(X(t), Q(t)\right) \end{cases} \tag{11}$$

In the closed-city model, U_0 can be determined endogenously. In the open-city model, U_0 is usually set as exogenous [22]. In Eq. (6) and Eq. (11), Y and U_0 are exogenous parameters. Y can be considered as the average income level in a given region (e.g. census tract). U_0 can be interpreted as the minimum living standard or quality of life in the region given the income level Y. The idea is that Y and U_0 are not two independently determined parameters. The two parameters can also be interpreted at individual household level.

The optimum conditions in Eq. (11) are similar to those of spatial equilibrium models, at least in the mathematical form. The essential difference is that the transportation cost now depends on the travel demand and transportation capacity from all previous stages of development. Put another way, the transportation cost for residents in the newly developed region now reflects the congestion effects created when they pass through all previously developed regions on the way to the CBD. Since traffic congestion is a mutual effect, from a social planner's perspective, therefore, the extra transportation cost imposed on residents located in previously developed regions by the congestion effects also needs to be taken into account.

ABM Simulation: Land Development and Congestion

The trade-off between transportation capacity and congestion does not disappear as long as there exists land scarcity. Traffic congestion is a price that urban residents have to pay for taking the advantage of concentration of amenities and economic activities by living in cities. Congestion, as the result of many individual trip decisions, driving habit, and transportation mode choices, is a complicated phenomenon to model. As Lindsey and Verhoef [28] point out, there is no single best way to model traffic patterns and congestion. For the purpose of modeling land use and transportation planning, it is adequate to capture only the main stationary relationship. In this section, an ABM simulation is implemented based on the monocentric urban spatial structure.

The goal of ABM simulation is to explore emergent properties out of a complex and open-ended system. In the context of urban modeling, ABM complements spatial equilibrium based models in both behavioral foundation (or micro-diversity as in Crooks et al. [11]) and system dynamics. There are three main components in an ABM simulation: stochastic component, decision making mechanism, aggregated representation. Stochastic components are the input to the model, which drives the process dynamics. Decision making mechanism, usually built upon a set of rationality and behavioral assumptions and optimization theory, is a simplified description of the individual behavior. Aggregated representation is more about output analysis. The results of ABM simulation are often not as neat as those of analytical equilibrium models. Therefore, certain level of aggregation (e.g. graphical and statistical analysis) is necessary to interpret the results and their implications. One of the concerns on ABM simulation practice is that the theoretical implications of many simulation models often remain implicit and hidden behind the mask of ad hoc assumptions about model structure and system process [11]. Therefore, it is imperative to clarify and lay out these major components in ABM simulations.

In the ABM simulation developed below, the stochasticity comes mainly from the population (consists of agents) growth process and household (agent) income variations. The decision making mechanism is designed basing on the open-city model developed in section "Transportation and Congestion: An Application". For computational purpose, some aspects of the structural model may be simplified.

Simulation Setup

In this ABM example on congestion cost, the landscape for model development is a monocentric circular city which consists of a CBD region in the center and residential regions surrounding the CBD. To study the urban land development dynamics, the simulation starts from a city with zero population and none residential development at the beginning. The development process of the city includes two sub-processes: population growth and new land development, which are also where the potential stochastic components come into play. Instead of modeling a birth-and-death process, the simulation only focuses on the net population growing process, which is assumed to follow a stochastic arrival process. The income level of each agent (i.e. household) is drawn from a statistical distribution that defines the range of income across the city.

Another important input to the simulation is the amount of land devoted to residential development and transportation capacity in each region. Transportation capacity can be considered as a local public good, which also has spillover effects (by reducing congestion effects) to households from other regions. If the provision of transportation capacity is funded through property tax (by taxing housing expenditure), then there exists an optimal level of ν—the proportion of land devoted to transportation capacity. The determination of a socially optimal ν is not straightforward, because ν apparently depends on the total (taxable) housing expenditure. At the same time, each individual household's housing expenditure depends on the transportation cost and therefore ν. To simplify, changes of ν can be considered as exogenous policy shocks. In this simulation, ν is assumed to follow an exogenous distribution with respect to distance t (to be discussed later).

The core element of the decision making mechanism is the household utility function. For each household, the disposable income is allocated to three different expenditures: housing, non-housing, and transportation. Given a constant α—the proportion of households working in the CBD, basing on Eq. (10) transportation cost is same for all households within a given region. Therefore, there are only two decision variables left in each household's consumer problem. The household decisions on housing and non-housing consumptions are made basing on the optimal conditions in Eq. (11)[5]. In this simulation a Cobbs-Douglas utility structure is specified [29], that is

$$U(X, Q) = \gamma_0 X^{\gamma_X} Q^{\gamma_Q} \tag{12}$$

where γ_0, γ_X, and γ_Q are constant parameters. While each household is differentiated by its income level, households may also be differentiated through the relative preference on housing and non-housing consumption, i.e., choosing different γ_X and γ_Q. Upon solving the household optimization problem, for each residential region t, all individual optimal housing consumptions constitute the aggregated housing consumption. The total land available for residential development in region t is given by $2\pi t(1 - \nu(t))$. Denoting the aggregated housing consumption in region t as $\sum_{i=1}^{h} Q_i^*(t)$, with h being as the total number of households in the region, $Q_i^*(t)$ the optimal housing consumption, then a measure for residential development density (ρ) in the region can be defined as:

$$\rho_t = \frac{\sum_{i=1}^{h} Q_i^*(t)}{2\pi t\,(1 - \nu(t))} \tag{13}$$

The residential development density, that measures the tension between residential land demand and supply, is an emergent property in this simulation. More specifically, the ABM simulation can help to illustrate the dynamic relationship between transportation cost and land development density, as well as the development density distribution with respect to distance. The change of development density from the scenario with congestion effects to the scenario without congestion effects is also interesting to explore.

Another interesting emergent property in this simulation is the housing price dynamics. As being implicit in Eqs. (6) and (11), the (unit) housing price in the analytical model is endogenously determined. The housing price solved through Eq. (11) is the individual willingness to pay for housing of each household. The existence of such heterogeneity of housing prices within a region can be explained by the residential sorting process [30]. Within a given region, households who are willing to pay more for a unit of housing are more likely to reside at location with better amenities or public services. Through the sorting process, household location choices within the region therefore reflect their willingness to pay. In this simulation, the micro sorting process is not explicitly modeled. There are two ways to look at housing price: (1) the cross-sectional housing price distribution within each region;

[5]Even though the optimal conditions here are derived to maximize land rent from a representative household (or social planner)'s perspective, they are equivalent to those first order necessary conditions of a household expenditure minimization problem. The minimized expenditure equals exactly to the household disposable income net of transportation cost which depends only on distance t. The reason for this result is that housing price is endogenous in the model, which exhausts any disposable income net of non-housing and transportation expenditure

(2) the distribution of housing price with respect to distance. In spatial equilibrium models, there exists a basic trade-off relationship between transportation cost and housing price, so that households are indifferent between locations across the city. In the proposed ABM simulation model, given the existence of congestion effects, how the relationship would change becomes a policy relevant question. So does the relationship between housing price and development density.

Parameterization

In this simulation, both the dynamic nature of the system and the open-ended environment of the model define a terminating simulation—the urban system is unlikely to reach a steady state. Given the setup of the model, two criteria can be chosen to terminate the simulation: (1) the simulation terminates after average housing price reaches certain level, for example, its opportunity cost—agricultural rent; (2) the simulation terminates after the city expands beyond a given boundary (e.g. $t \leq 10$). Depending on the goal of simulation, either criterion can be a reasonable choice.

The values of all key parameters in the simulation are set based on the scenario of large U.S. metropolitan areas. According to the U.S. Bureau of Labor Statistics Consumer Expenditure Survey in 2011, for instance, urban households on average spent \$50,348; and \$17,226 of which was on housing consumption, \$2586 of which was on transportation. Given this empirical evidence on income allocation, the parameters γ_X and γ_Q are set to 0.5 and 0.3, respectively[6]. According to Arnold and Gibbons's [31] analysis of urban impervious surface coverage, about $5-10\%$ of suburban land, $20-30\%$ of urban land, and $40-60\%$ of commercial center land is devoted to roads and parking. Therefore, the proportion of land devoted to transportation capacity, $\nu(t)$, is specified as a decreasing function of distance t in the range of $5-40\%$. Similar to Wheaton [22], the parameter β in the transportation cost is set to 1.1, which is a very conservative specification on congestion effects. Further sensitivity analysis can be performed to explore the impact of parameter choices. All simulation parameters are summarized in Table 1.

Simulation Results

The simulations are programmed in MATLAB and implemented on a 64-bit Windows 7 operating system, with a 3.40 GHz Intel Core i7–2600 processor and 12.0 GB RAM. For a simulation (with graphing) with both congestion scenario and

[6]The parameter 0.5 and 0.3 are chosen based on relative income allocation. 0.5: 0.3 $\approx$ non-housing consumption net of transportation cost: housing consumption

Table 1 Parameters in the ABM simulation

Variable	Value	Definition
T	10	Number of residential regions
POP_t	Triangular (2,5,4)[a]	Net population growing process (in 10,000)
γ_0	1	Utility function parameter
γ_X	0.5	Utility function parameter
γ_Q	0.3	Utility function parameter
k	0.01	Transportation cost function parameter
m	1.1	Transportation cost function parameter
α	0.5	Proportion of households working in the CBD
$v(t)$	$\left(40 - \frac{35(t-1)}{T-1}\right)\%$	Land devoted to transportation capacity
Y	Uniform [30,000,100,000]	Household income level
U_0	$U_0 = Y/2$	Household desired utility level

[a] All generated numbers are rounded to integers

no congestion scenario[7], the simulation CPU time ranges from 100 to 130 seconds. Given the range of the city, the CPU time increases with the number of agents (population size). There are two major endogenously determined variables in this simulation: housing price and transportation cost. The two variables are also highly policy-relevant.

The housing price distributions (kernel density estimation with Epanechnikov kernel and optimal bandwidth) are presented in Fig. 1. Due to space limitation, four regions (1, 4, 7, 10) are included only. All housing prices are standardized (divided by the maximum price and multiplied by 100) so that the maximum price equals to 100. Note that the graphs only show the relative distribution of housing prices within each region, which varies from region to region. As the distance to the CBD increases, moving from the CBD to suburban area, the price distribution becomes less skewed. That is, housing price is more uniformly distributed across households in suburban area. One possible explanation for this phenomenon is that, given household income follows a uniform distribution, in the suburban area household income level has more impact on the willingness to pay (individual housing price) for housing consumption.

Another way to look at housing price is through the aggregate housing price level in each region. Figure 2 shows the relationship between aggregate housing price and distance to the CBD. The dashed line (red) indicates an approximately negative linear relationship between housing price and distance to the CBD under no congestion scenario (see footnote 7). Under no congestion scenario, the marginal price change with respect to distance to the CBD is constant. With congestion effects

[7]In the congestion scenario, the transportation cost is calculated according to Eq. (10). In the no congestion scenario, the transportation cost per unit distance is set equal to the transportation cost at $t = 10$ under congestion scenario divided by 10. In other words, at region $t = 10$, the total transportation costs in both scenarios are the same (see Fig. 3)

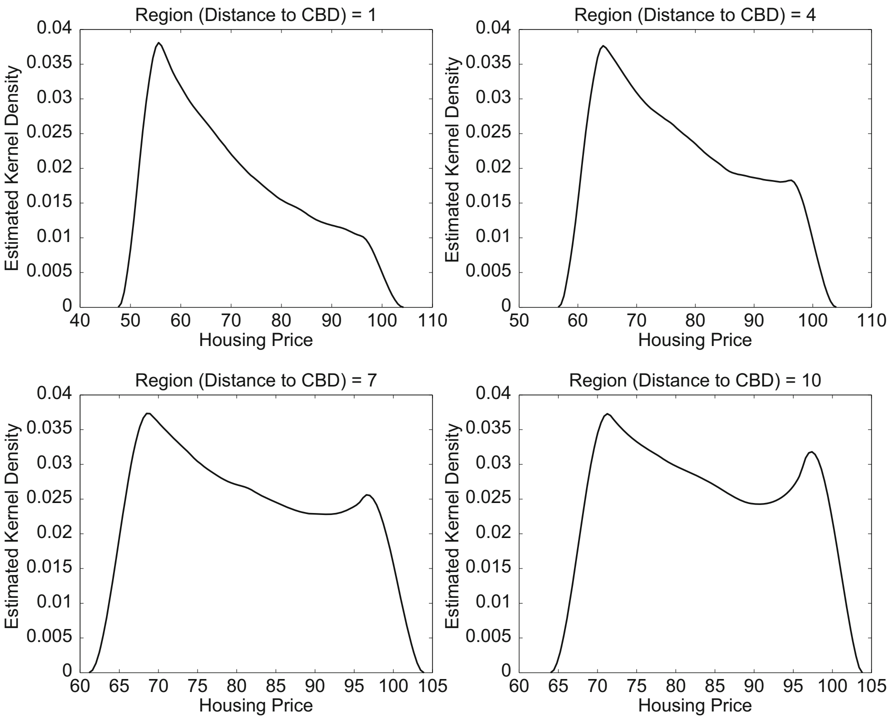

Fig. 1 Housing price distribution at different regions. Note: All housing prices are standardized with maximum price equals to 100. The density curves are kernel estimation with Epanechnikov kernel and optimal bandwidth

considered, housing price decreases quickly first, and then slows down as moving further from the CBD. Under the congestion scenario, the housing price level change reflects both a distance effect and a congestion effect. Both effects lower the housing price. The distance effect reflects the fact that, the further moving from the CBD, the higher the transportation cost and therefore the lower the housing price. The congestion effect, on the other hand, has a diminishing effect. In the regions near to the CBD, congestion tends to be more severe thus dominates the distance effect. This can be seen from the part where the solid (blue) line is under the dashed line (red) in Fig. 2. In the regions far from the CBD, the congestion effect is reduced and the distance effect becomes dominant.

The change of transportation cost works in the opposite direction to the change of housing price. According to the spatial equilibrium principle, if something is attractive in one location, then we should expect to see something unattractive offsetting it in the same location [32]. In this model, housing price and transportation cost offset each other. In Fig. 3, the dashed line (red) shows the transportation cost without congestion effects, where total transportation cost is in a direct relationship with distance to the CBD. The marginal transportation cost in this case is constant

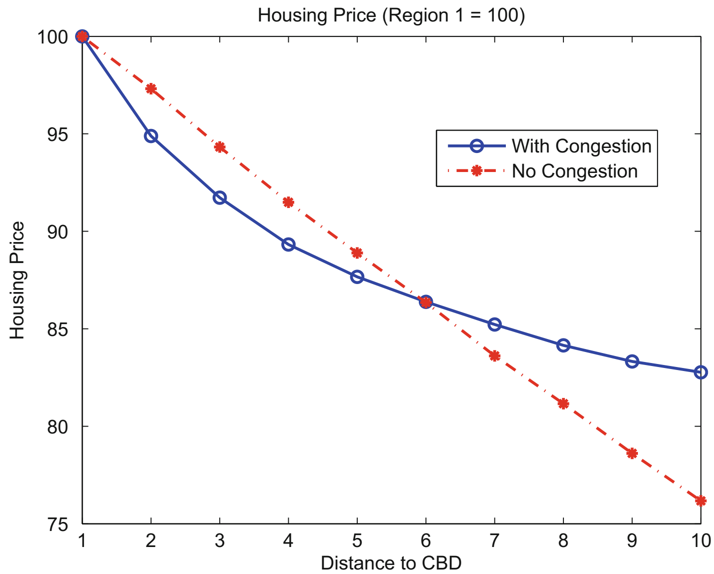

Fig. 2 Average housing price and distance to the CBD. Note: The aggregate housing prices are standardized with the price in region 1 equals to 100

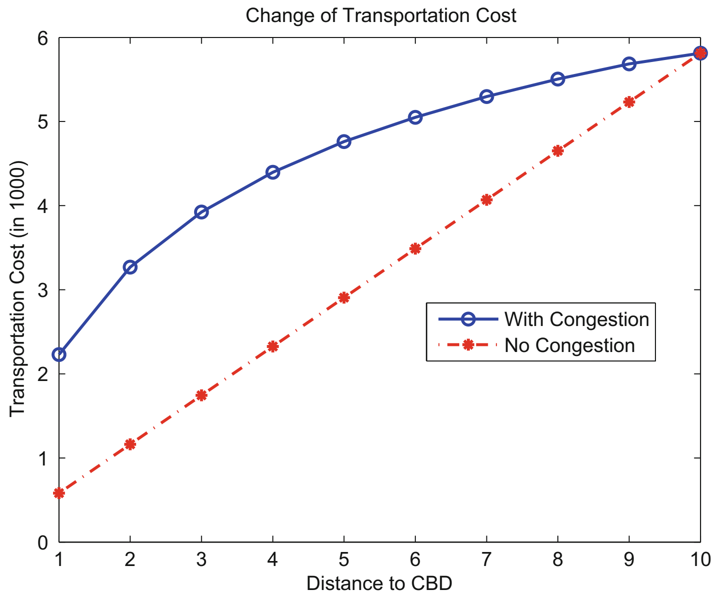

Fig. 3 Transportation cost and distance to the CBD

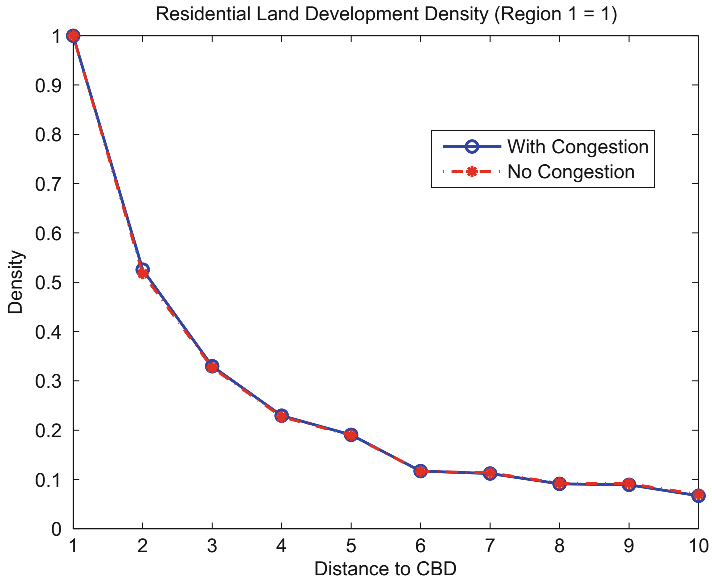

Fig. 4 Residential land development density and distance to the CBD. Note: The density measure is standardized with density in region 1 equals to 1

(see footnote 7). When there are congestion effects associated with travel, the total transportation cost becomes higher as expected. The diminishing trend of marginal transportation cost in this case reflects the fact that congestion effect is reduced as households reside further from the CBD. One other result to note is that, the difference between transportation costs under two different scenarios is not maximized at region 1. The maximum difference is reached around region 3.

As discussed in section "Simulation Setup," another way to explore the simulation outcome aggregately is to look at residential development density in each region. In this model, both the housing demand side (population) and housing supply side (amount of land in each residential region) are exogenously determined. Given that these two factors directly determines the pressure on land development, thus the land development density is likely to follow an exogenously determined pattern as well. In other words, the existence of congestion effects should not have a strong impact on land development density across all regions. The results presented in Fig. 4 confirm this conclusion. In Fig. 4, the development density measure is standardized (divided by the maximum density) with density in region 1 equals to 1. The development density under two different scenarios is almost overlapping with each other, even though there indeed exists small differences (see Table 2). Note that the congestion effects are also a function of distance and the size of the city (e.g. the radius of urban area in reality), which becomes important especially in an open-city model.

Table 2 Residential land development density and distance to the CBD

Region	1	2	3	4	5	6	7	8	9	10
With congestion	1.0000	0.5255	0.3295	0.2292	0.1905	0.1167	0.1120	0.0912	0.0890	0.0668
No congestion	1.0000	0.5178	0.3267	0.2270	0.1893	0.1164	0.1133	0.0925	0.0913	0.0694

Note: all numbers reported are corresponding to Fig. 4

Discussion

The advantage of the ABM simulation approach to urban systems is that it has a solid behavioral foundation of individual decisions. Depending on the context of modeling, the simulation procedure still needs guidance on model structure from analytical approach. In the simulation model presented above, we have incorporated urban spatial structure models and spatial equilibrium theory into simulation. The strength of these independent theories is that they provide simplified and structural ways to understand a complex system. Built upon which, simulation models can become a powerful tool in facilitating structural understanding of urban systems while with adequate level of spatial details.

The current model still hinges on the classic monocentric urban spatial structure with homogeneous landscape. The limitations of such models could be relaxed in at least two ways. First, the literature has long been paying attention on the development of non-monocentric models. The difficulty with developing non-monocentric urban spatial structure is mainly on the analytical treatment of spatial dimensions. This could be a bottleneck in integrating the analytical approach and the ABM approach, but it also points to a fruitful future research direction. Another development in the literature that could help to refine the modeling of urban system dynamics is the residential sorting process. The entire urban area may never reach an equilibrium. At a smaller scale, however, households can sort across different locations (e.g. within a community) and reach a local equilibrium. This requires urban simulation to take into account the existence of microstructures within the urban system.

Sensitivity analysis, which many existing ABM simulation models fail to emphasize, is an important part of aggregate representation. In some sense, sensitivity analysis is as important as parameter calibration. In every simulation model, certain parameters have to be exogenously given or calibrated. The sensitivity of simulation results with respect to the choice of exogenous parameters is necessary knowledge for understanding the results. In the model presented above, parameter m—a transportation cost parameter—is an important parameter to the model [22]. Figs. 5 and 6 show how the change of m (from 1.0 (Fig. 5) to 1.2 (Fig. 6), the default value in the model is 1.1) influences the main results of simulation.

Combining Figs. 2, 3, 4, 5, and 6, as parameter m changes, we can see that the main patterns of housing price, transportation cost, and development density

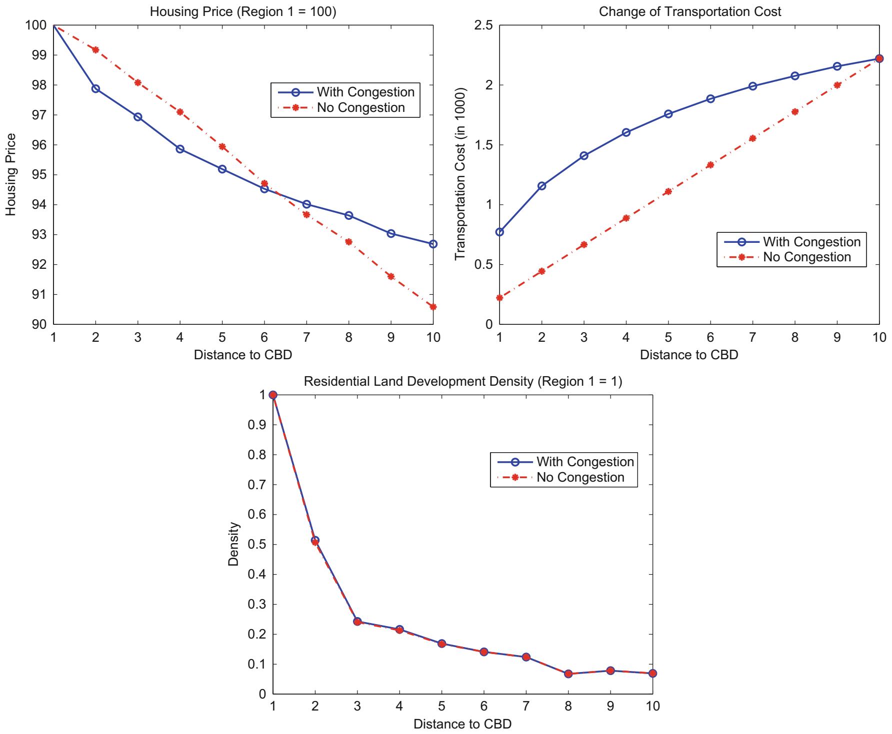

Fig. 5 Sensitivity analysis on transportation cost parameter m ($m = 1.0$)

between congestion scenario and no congestion scenario still hold. The noticeable changes in the results are mostly from the magnitude of specific measures. Therefore, as far as the specification on transportation cost function is concerned, the simulation results are robust. Similarly, sensitivity analysis on other key parameters (e.g. proportion of households working in the CBD) can be performed.

Relating to the model in this chapter, the commuting cost in the city also depends on the travel route choice. In this chapter's simulation model, the transportation system consists of symmetric ray-style routes and all households choose the shortest route to commute. An alternative scenario would be allowing households to choose among different travel routes. Unless the urban configuration is asymmetric and heterogeneous, then there is only negligible difference between the two scenarios. On the other hand, allowing for travel mode choice could lead to substantial difference in the outcomes, because different travel modes directly imply different levels of transportation cost given other factors.

Though the simulation model is only for illustration purpose, we can still learn some policy implications from the outcomes. The first policy-relevant result is the underestimate of transportation cost (in classic spatial equilibrium models) and

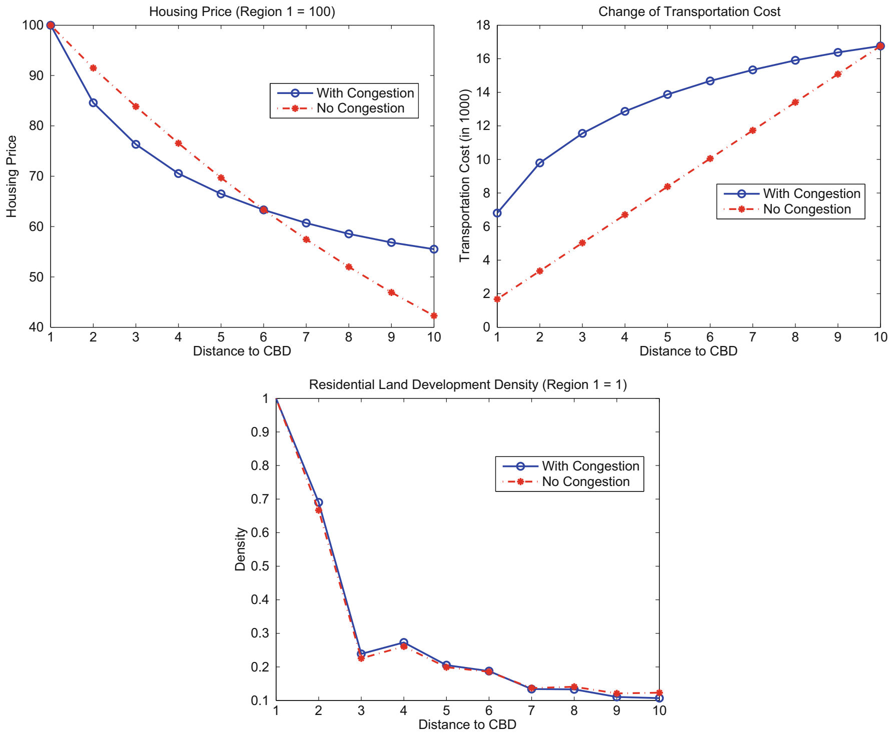

Fig. 6 Sensitivity analysis on transportation cost parameter m ($m = 1.2$)

the nonlinearity of transportation cost, as shown in Fig. 3. The underestimate of transportation cost is due to the ignorance of congestion cost. The ABM simulation helps to inform the nonlinearity of transportation cost, which is valuable for designing and evaluating public transportation system. A land use policy-relevant result is that land development density is insensitive to the existence of congestion costs (Fig. 4). This on the other hand implies that land development density depends more on overall urban spatial structure and demographics. Therefore, both economic planning and land use planning have important impacts on land use density.

Concluding Remarks

The modern city is an arrangement between its residents and local governments from both an institutional and a financial perspective. Seeking for efficient public policy and proper government intervention is essential to the sustainability of such an arrangement. Because of the mobility and heterogeneity of the population, it is often difficult to keep track of all individual household location and consumption decisions. On the other hand, public policy tends to provide general prescription for diversified individual preferences. How to aggregate the individual preferences into a form that policy makers can practice on is a critical task of urban modeling. The ABM simulation approach proposes a way to visualize urban systems so that well-founded social and economic implications can be derived to inform public policy-making. Though the multi-agent systems introduce solid behavioral foundation to urban modeling, the current urban simulation methodology still needs emphasis on structural understanding of urban systems. White and Engelen [33] raise two major concerns on high-resolution simulation models of urban and regional systems, for example, regarding the evaluation of simulation results and model predictability. One solution to address these issues is to incorporate urban spatial structure theory into urban simulations, which is the main theme of this chapter.

In this chapter, the linkage between major components of urban simulation and urban spatial structure models are discussed. Upon which, an ABM simulation model of urban land development is proposed with focus on transportation cost and congestion effects, to illustrate the role of urban spatial structure in urban simulation. The goal of the chapter is twofold. The first goal is to stress the importance of analytical modeling as the skeleton of urban modeling, even with the simulation approach. A modular architecture of urban simulation is not necessarily informative regarding results evaluation and model predictability. A further goal is to emphasize how urban spatial structure models can help to integrate household behavior, individual decision making, and aggregate model representation together. The simulation example provided in the chapter, though only for illustration purpose, gives at least some sense on how the combination of analytical modeling and ABM simulation can be an efficient and informative approach to urban modeling.

Still, there are many challenges ahead in urban modeling. For example, the development of theories on social interactions, networks, and matching mechanisms has substantially pushed the limit of our knowledge on human behavior and system dynamics. How to incorporate these new research into urban modeling is both a theoretical question and an empirical matter. Another under-researched area of urban simulation is the model calibration, which plays a critical step towards good model predictability. Similarly, calibrating model specification and parameters is also both a theoretical issue and an empirical issue. All these challenges and therefore potential future research directions will certainly have profound impacts on urban and regional modeling.

Lastly, the focus of the chapter is to suggest how we could use well-established urban spatial structure models in economics and urban studies to strengthen current agent-based urban simulation studies. The chapter does not intend to criticize current urban spatial models. Instead, the chapter argues that we should incorporate them to improve current agent-based urban simulation practices.

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