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Travel time reliability, urban form, decision making under uncertainty and smart urban development

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ABSTRACT: Within a land use-transportation interaction model, this study embeds a behavioral framework which accommodates travel decision making under uncertainty into a spatial general equilibrium model to understand the interplay between individuals' mode choices and urban form. Special attention is paid to demonstrating the multifold role of ambiguity attitude, a behavioral mechanism existing in real-market decisions but largely overlooked in urban models. Our baseline model outputs are consistent with the market evidence, which reinforces the rationality of the proposed model with a focus on behavioral realism. We also simulate the possible impacts of improved travel time reliability on system behavior and urban form, and the results suggest it is possible to realize smart development in terms of sustainable travel and city growth.

KEY WORDS: ***Land use-transportation interaction; urban form; decision making under uncertainty; ambiguity attitude; travel time reliability***

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1. Introduction

Land use offers opportunities or resources at a given location, and various transport systems allow citizens to access them at different costs. Urban form and travel behavior are intricately intertwined, resulting in dynamics in mobility (Van Acker, 2021; Wallner et al., 2018). The spatial distribution of economic activity determines the underlying traffic patterns in the urban network; in the meantime, travelers' choices can also shape traffic patterns and affect the spatial distribution of economic activity (Allen & Arkolakis, 2022). The interaction between land use and transportation lies at the intersection of urban economics and transport economics (Dong et al., 2022; Ng & Lo, 2017; Franco, 2017; Anas & Kim, 1996). The purpose of land use-transportation interaction (LUTI) models "is to encompass travel behavior in their workings so that future policies can be evidence based" (Mulley & Nelson, 2021, p.5), which emphasizes that a key challenge is to mimic real-life travel decision making in these models.

Real-world travel choices are made under uncertainty, mainly due to travel time variability (Tirachini et al., 2022; Hensher et al., 2015). The underlying behavioral foundation for utility-based LUTI is random utility maximization (RUM) (Engelberg et al., 2021). Engelberg et al. (2021, p.383) highlight that: "this reliance on the estimation of a choice model is simultaneously the weakness of utility-based accessibility measures. Specifically, the measures are only as accurate as the underlying model and its assumptions, data, and specification choices". RUM implicitly assumes risk neutrality and ambiguity neutrality through its linear utility functional form, which has been criticized for its inability to fully capture the underlying decision-making processes that result in observed choice outcomes, especially in uncertain situations (Li & Hensher, 2020). Moreover, travel time reliability or the probability of arriving on time significantly affects the level of accessibility experienced by travelers, and therefore, it is essential to accommodate it when measuring accessibility that is jointly determined by land use and transport systems (Bimpou & Ferguson, 2020). To the best of the authors' knowledge, when modeling the interaction between transportation and land use, important behavioral mechanisms such as ambiguity and risk attitudes that characterize individuals' decision-making patterns in the presence of travel time variability have been largely overlooked in the relevant literature. The absence of these important parameters may lead to biased findings on behavioral reactions to pricing schemes, technological advancements or unanticipated events.

In this paper, we draw on theories focusing on decision making under uncertainty to lay a foundation for establishing the connection between commuters' mode choices in the presence of travel time variability at the micro-level and urban form at the macro-level. Uncertain choice behaviors are determined by two important mechanisms, namely risk attitude and ambiguity attitude. The former reflects a preference (positive, neutral or negative) for a risky alternative over a sure one with an equivalent expected value. The latter captures the different responses towards unknown vs. known probability distributions, and it is a relative measure. Specifically, we develop a mode choice model with a focus on endogenous commuting costs influenced by commuters' choice behaviors, and combine it with a spatial general equilibrium model. The transport sub-model calculates travel times during commuting in which commuters' behaviors are shaped by their preferences and attitudes. The land use sub-model addresses the land-use decisions of firms and households with consideration of endogenous travel costs and agglomeration externalities. We apply the model system to an Australian city, Hobart. By comparing the model outputs with the available market evidence, the credibility of our proposed model is demonstrated. In the fields of urban economics and transport economics, there has been a growing number of studies that have investigated the impact of emerging and more reliable transportation on land use patterns (e.g., Liu et al., 2021; Larson & Zhao, 2020; Moore et al., 2020), calling on more research in this context. This has motivated us to conduct 'what-if' scenario analyses to investigate the impact of improved travel time reliability on urban form. Our simulation suggests that improved reliability or reduced variability would promote the modal switch from private cars to public transport where commuters' stronger ambiguity seeking towards the latter source of uncertainty plays a prominent role, and facilitate the smart urban development.

The remaining parts of the paper are organized as follows. Section 2 reviews the relevant literature. Section 3 presents the modeling framework of this study. Section 4 presents the simulation results of the case study. Section 5 concludes this paper with key findings.

2. Literature review

Accessibility is a key variable that integrates land use and transportation. Geurs & van Wee (2004, p. 128) defined accessibility as the "extent to which the land-use and transportation systems enable individuals to reach activities or destinations". Accessibility comes at a cost of travel, which composes of time and money spent on the trip that directly affect accessibility including choices of home location and workplace. Considering the complexity of transport systems, some studies have developed travel cost functions that account for the unique characteristics of each travel alternative (Zheng & Geroliminis, 2020; Gelauff et al., 2019; Ng & Lo, 2017). The differences in travel costs are also studied at the route level. For example, Allen and Arkolakis (2022) specified travel costs according to the traffic congestion and traffic infrastructure. Despite these improvements, a rather crucial missing element in forming the utility function for generalized travel costs is ambiguity attitude.

Ambiguity attitude is the behavioral mechanism that distinguishes between choice behaviors under uncertainty with subjective probabilities and under risk with objective probabilities or across various sources of uncertainty (Abdellaoui et al., 2011; Wakker, 2010). Various theoretical models have been developed to accommodate ambiguity attitudes, including Maxmin expected utility (MEU, Gilboa & Schmeidler, 1989), Choquet expected utility (CEU, Schmeidler, 1989), α-maxmin expected utility (α-MEU, Ghirardato et al., 2004) and contraction expected utility (Gajdos et al., 2008). According to the comparative ignorance hypothesis (Fox & Tversky, 1995), decision making is not only affected by the degree of uncertainty, but also the source of uncertainty which plays an even more important role in decision making (Li et al., 2018). Source preference captures the difference between beliefs for subjective probabilities generated from different sources of uncertainty. Based on this hypothesis, Fox & Tversky (1998) developed a general belief-based account model for decision making under uncertainty with two essential components: (1) the analysis of risky choices and (2) the elicitation of source preference (Abdellaoui et al., 2021; Aydogan, 2021).

Findings from the broader literature reinforce the significant role of ambiguity attitudes in various decisions, such as economics (Luo et al., 2021; Guillemin, 2020; Brenner & Izhakian, 2018), agriculture (Tevenart & Brunette, 2021; Crentsil et al., 2020; Bougherara et al., 2017), climate policy (Etner et al., 2021; Chambers & Melkonyan, 2017; Petr et al., 2016) and health (Stuart et al., 2022; Courbage & Peter, 2021; Fujii & Osaki, 2019). Ambiguity attitudes are found to be related to the probability distribution of losses/gains (Kocher et al., 2018), and a fourfold ambiguous attitude pattern has been revealed: ambiguity aversion for moderate-high likelihood gains or low likelihood losses and ambiguity seeking for low likelihood gains or moderate-high likelihood losses (Kocher et al., 2018; Bouchouicha et al., 2017; Ozdemir, 2017; Baillon & Bleichrodt, 2015). In the field of travel behavior research, Qi et al. (2016) developed the ambiguity-aware CARA (Constant Absolute Risk Aversion) travel time model to solve the route selection problem in an uncertain setting. Kemel and Paraschiv (2013) interpreted commuters' ambiguity-seeking behavior as a preference for irregularity of service frequencies. Hensher et al. (2015) applied Fox and Tversky (1998)'s model to describe the process of commuters' travel mode decision making with their subjective probabilities. Li et al. (2022) investigated the role of information in shaping traveler's ambiguity attitudes within an improved Rank-Dependent Utility Theory model, and found that commuters exhibit stronger ambiguity seeking for public transport (PT) trips than that for car trips. These empirical findings suggest that travelers' 'true' attitudes should be addressed in urban models so that policy implications can be evidence based. However, ambiguity attitude that exists in real-market decisions has been ignored in the existing LUTI literature (see Table 1 and the review paper by Engelberg et al., 2021). In developing the next generation of LUTI models, Engelberg et al. (2021) call on for a more realistic representation of actual travel choice behaviors. Ilut & Schneider (2022) highlight the need for future research on modeling uncertainty to embed ambiguity into a wider variety of models with uncertainty.

Table 1: A summary of some recent land use-transportation interaction studies

	Purpose	Ambiguity attitudes	Risk attitudes
Ng & Lo (2015)	To study the influence of housing supply on residential choices and travel choices	No	No
Zhang & Kockelman (2016b)	To examine the impacts of congestion and subsidy on firms' and households' land-use decisions	No	No
Ng & Lo (2017)	To understand the relationship between housing development and railway development	No	No
Jin et al. (2017)	To examine the environmental impacts resulting from land use and transport developments	No	No
Li et al. (2017)	To investigate the optimal toll with the consideration of heterogeneous households' residential choices	No	No
Vandyck & Rutherford (2018)	To investigate the indirect effect of time-invariant congestion charges on welfare	No	No
Zhu et al. (2018)	To study the impact of cumulative land development	No	No
Gelauff et al. (2019)	To explore the spatial effects of self-driving and its welfare	No	No
Li et al. (2019)	To evaluate the urban expressway system with the consideration of the interaction between transportation and land use	No	No
Hensher et al. (2020)	To introduce MetroScan and explore the economic impacts of reduction in bus fares	No	No
Liu et al. (2021)	To estimate the role of autonomous vehicles on the traffic equilibrium and urban form	No	No
Huai et al. (2021)	To explore the impacts of activity resource allocation or dispersion, transport improvement, and property development	No	No
Allen & Arkolakis (2022)	To assess the welfare gains of transportation infrastructure improvements	No	No

3. Model framework

The interaction between transportation and land use is a complicated feedback loop (Allen & Arkolakis, 2022). To capture the reciprocal activities, we define a model system shown as Figure 1, in which travel cost is the key to connecting the transport sub-model and the urban land use sub-model.

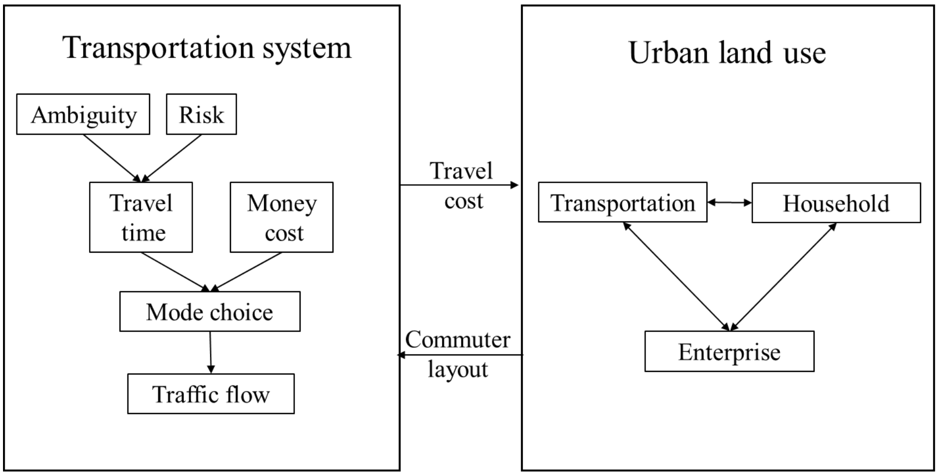

Figure 1: Model framework

Following Lucas & Rossi–Hansberg (2002), a city is treated as a circular region with a uniform mass and a fixed city boundary x_L (Figure 2). It is divided into L segments of narrow rings with the same width Δx from the center to the periphery. There are N commuters living in the closed system, and they travel from one ring to another. There are some arterial roads in the city, which share the whole commuting volume evenly. We can select one of the roads with n commuters as a representative sample when estimating each zone's travel cost. According to the segmentation of the city, the example road is also divided into L segments; The farther away from the CBD, the higher the area is numbered. For example, the selected road is numbered to be 'R_1'in the most central area (i.e., the CBD), and road segment at the distance from the lth area to the CBD (x_l) can be denoted as R_l. For all locations, three main modes are considered: car, bus and rail, subject to travel time variability. In addition, we also make the following assumptions.

a. Firms are homogeneous when making all choices.

b. Housing decisions are homogeneous across households.

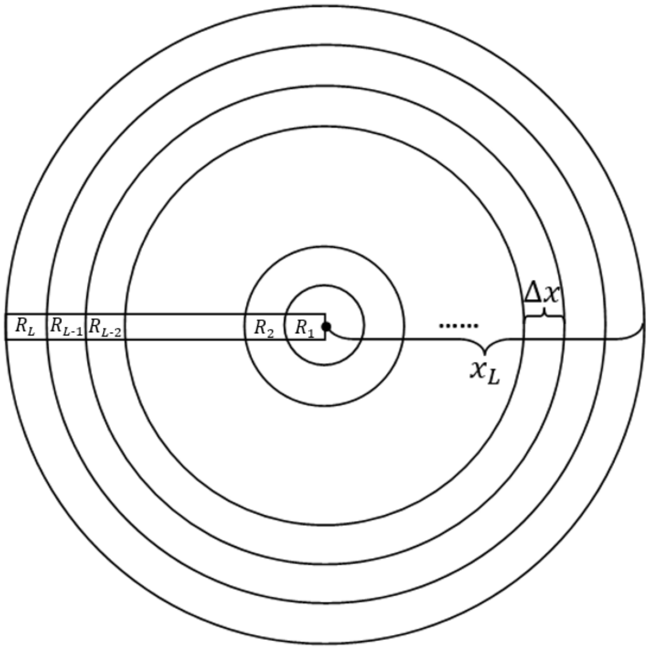

Figure 2: The illustrative description of a city in the land use model

The urban land-use model follows Zhang and Kockelman (2016a); while we modified it into a discrete form including land use decisions of households and firms, and the general equilibrium conditions in the land market and the labor market.

3.1 Household's land use decision

Suppose the population keeps unchanged in the closed system, and the revenues (land rent) are redistributed equally to all residents. Assuming there is only one household member being employed per household, the home location of household i is x $(0 < x < x_L)$ and the job location of this household is x_w $(0 < x_w < x_L)$. A household living in a house with a size of q maximizes utility according to:

$$\max_x U = C(x, x_w)^\eta q(x, x_w)^{1-\eta}, \tag{1}$$

subject to the budget constraint:

$$C(x, x_w) + r_h(x) q(x, x_w) \leq\ y(x, x_w) = w(x_w) + \frac{1}{N} y_{rent} - TC(x, x_w), \tag{2}$$

where C is the consumption of non-housing goods; η is the elasticity parameter of the utility function; r_h is the rental rate; $y(x, x_w)$ is the net annual income of a household which consists of three components: wage income paid by a firm at location x_w [$w(x_w)$], the return of aggregate rent revenues [$\frac{1}{N}y_{rent}$], and the annual commuting cost from x to x_w [$TC(x, x_w)$]; N is the total number of households in the city.

The equilibrium value of each variable in the model is assumed to be independent of its working location, hence:

$$y(x, x_w) = y(x) = w(x) + \frac{1}{N}y_{rent}, \tag{3}$$

$$C(x, x_w) = C(x), q(x, x_w) = q(x). \tag{4}$$

In order to satisfy equation (3), the increase (decrease) of an individual's travel cost resulting from the job location change needs to result in an equivalent reduction (increment) in the wage. As such, the condition as shown in equation (5) must meet:

$$w(x_w) - TC(x, x_w) = w(x_c) - TC(x, x_c), \forall\, x, x_w. \tag{5}$$

Let $x = x_c$, then

$$w(x_w) \;\; = w(x_c) + TC(x_w, x_c), \tag{6}$$

where x_c is the location of the CBD.

Under the assumption of equilibrium, the optimal house area located at x for a household is:

$$q^*(x) = \eta^{-\eta/(1-\eta)}y(x)^{-\eta/(1-\eta)}\bar{u}^{1/(1-\eta)}, \tag{7}$$

where $\bar{u}$ is the individual utility solution of the optimization problem (see equation (1)) in equilibrium.

The optimal consumption of non-housing goods is:

$$C^*(x) = \eta y(x), \tag{8}$$

and the maximum rent that a household is willing to pay is:

$$r_h^*(x) = (1-\eta)\eta^{\eta/(1-\eta)}y(x)^{1/(1-\eta)}\bar{u}^{-1/(1-\eta)}. \tag{9}$$

3.2 Firm's land use decision

For a firm located at x_w, its production capacity $B(x)$ can be expressed as a Cobb Douglas function: labor force $L(x)$ and land area $H(x)$:

$$B(x) = A(x)L(x)^{\kappa}H(x)^{1-\kappa} \quad (0 < \kappa < 1), \tag{10}$$

where κ is the elasticity parameter; $A(x)$ is total factor productivity, which is related to the agglomeration externality $F(x)$, as shown in equation (11):

$$A(x) = \sigma F(x)^{\gamma}, \quad (0 < \gamma < 1), \tag{11}$$

where σ is the productivity scale parameter; γ is the elasticity of productivity with respect to agglomeration externalities at location x. The agglomeration externality is expressed as:

$$F(x) = \zeta \sum_{k=1}^{L} \Delta x * \int_0^{2\pi} x_k \theta_f\,(x_k) d(x_k)\, e^{-\zeta\sqrt{x_k{}^2 + x^2 - 2xx_k cos(\psi)}} d\psi, \tag{12}$$

where ζ is the production externality scale parameter, x_L is the distance from the CBD to the periphery, θ_f indicates the fractions of land area used by firms, $d(x) = \frac{L(x)}{H(x)}$ denotes employment density.

By normalizing the price of output to be '1', the firm's productivity decision can be described as a profit maximization problem:

$$\text{Max } \pi(x_w) = \sigma d(x_w)^{\kappa}F(x_w)^{\gamma} - d(x_w)w(x_w) - r_f(x_w), \tag{13}$$

where $r_f(x_w)$ is the land rent of a firm located at x_w.

The optimal employment density is:

$$d^*(x) = \left(\frac{\kappa\sigma F(x)^\gamma}{w(x)}\right)^{1/(1-\kappa)}, \tag{14}$$

and the maximum rent that a firm located at x is willing to pay is:

$$r_f^*(x) = (1-\kappa)\sigma^{1/(1-\kappa)}F(x)^{\gamma/(1-\kappa)}\left(\frac{\kappa}{w(x)}\right)^{\kappa/(1-\kappa)}. \tag{15}$$

3.3 Transport system embedded with risk and ambiguity attitudes

In Zhang and Kockelman (2016a), their travel cost (TC) is specified as an accumulation of marginal monetary costs, with a generic value for all modes. To allow for mode-specific travel costs, we take equation (16) as a mediator which connects daily commuting costs with commuters' mode choices. Furthermore, a modified iterative algorithm based on the nested fixed-point algorithm is proposed to solve the equilibrium outcome in the land use model (see Section 3.5). Our major improvement over existing urban simulation studies with endogenous travel costs (see e.g., Allen & Arkolakis, 2022; Liu et al., 2021; Xu et al., 2018) is that we take into account an extended set of behavioral characteristics from both economic and psychological perspectives, which may, in turn, improve the credibility of policy analysis at the macro-level. In doing so, we estimate the average annual travel cost from location x to the employment center with the highest job density ($TC(x)$), by using equation (16).

$$TC(x) = [tc_{car}(x) * P_{car}(x) + tc_{bus}(x) * P_{bus}(x) + tc_{rail}(x) * P_{rail}(x)] * Day * 2, \tag{16}$$

where $tc_{car}(x)$, $tc_{bus}(x)$ and $tc_{rail}(x)$ are the monetary cost per commuting trip from location x to the employment center with the highest job density by car, bus and rail, respectively; Day is the number of commuting days per annum, which is assumed to be 250. $P_{car}(x)$, $P_{bus}(x)$ and $P_{rail}(x)$ are the corresponding probabilities of these modes being chosen, which are estimated by equation (17) to (19). The utility of a commuter choosing a mode is shown in equation (20):

$$P_{car}(x) = \frac{exp\left(V_{car}(x)\right)}{exp\left(V_{car}(x)\right) + exp\left(V_{bus}(x)\right) + exp\left(V_{rail}(x)\right)}, \tag{17}$$

$$P_{bus}(x) = \frac{exp(V_{bus}(x))}{exp(V_{car}(x)) + exp(V_{bus}(x)) + exp(V_{rail}(x))}, \tag{18}$$

$$P_{rail}(x) = \frac{exp(V_{rail}(x))}{exp(V_{car}(x)) + exp(V_{bus}(x)) + exp(V_{rail}(x))}, \quad (19)$$

$$U(x) = \beta_t t^e(x) + \beta_c tc(x) + \varepsilon, \quad (20)$$

where $tc(x)$ and $t^e(x)$ are the monetary cost and commuter's perceived travel time of a commuting trip from location x to the CBD, respectively; β_c and β_t are their corresponding coefficients to be estimated; V indicates the observable component of utility; ε is the unobservable error term.

On the basis of Li et al. (2022)'s empirical findings estimated from a survey conducted in Australia, we use a source-dependent and rank-dependent utility function within which to model commuters' mode choices. Suppose that there are K possible outcomes of uncertain travel time for a trip which are ranked from the worst to the best $(t_1, t_2, \ldots, t_K)$ with the corresponding likelihoods being $(p_1, p_2, \ldots, p_K)$, subject to the conditions: $p_k \geq 0, k = 1, \ldots, K, \sum_{k=1}^{K} p_k = 1$. The expected travel time is a weighted sum of these possible outcomes, while the utility of the outcomes and the probabilities associated with the outcomes are subjectively influenced by individuals' preferences and attitudes:

$$t^e = \sum_{k=1}^{K} G(p_k) u(t_k), \quad (21)$$

$$u(t_k) = \frac{{t_k}^{1-\alpha}}{1-\alpha}, k = 1,2, \ldots, K, \quad (22)$$

where $u(\cdot)$ is the nonlinear utility function modeled with a constant relative risk aversion (CRRA) form; α is the risk attitude parameter to be estimated; $G(\cdot)$ is a probability-transformation function depending on the source of uncertainty.

Following Li et al. (2022), we embed the source function (Fox and Tversky, 1998) within a Rank-Dependent Utility model (Quiggin, 1982), and define $G(\cdot)$ as function that accommodates ambiguity attitude and risk attitude, as shown in equation (23).

$$\begin{cases} G(p_k) = [g(p_k + p_{k+1} + \ldots + p_K) - g(p_{k+1} + \ldots + p_K)]^{\theta}, k = 1,2, \ldots K \\ G(p_K) = [g(p_K)]^{\theta}, \end{cases} \quad (23)$$

where θ denotes the relative source preference of bus and rail relative to private car and can be used as an indicator of ambiguity attitude ($\theta > 1$ is inversely associated with the attractiveness of the source of uncertainty in the gain domain and *vice versa* (Abdellaoui et al., 2011)). $g(\cdot)$ is the probability weighting function, for example, the functional form proposed by Tversky and Kahneman (1992):

$$g(p_k) = \frac{p_k^{\psi}}{[p_k^{\psi}+(1-p_k)^{\psi}]^{\frac{1}{\psi}}}, \tag{24}$$

which transforms the cumulative distribution based on the rank of outcome into decision weights, according to the parameter estimation of ψ.

3.4 The general equilibrium conditions

3.4.1 Land market

When the land market reaches equilibrium, the rent at the city edge must equal the agricultural land rent R_a. The bid-rent of any location in the city is the highest bid among the households and firms in the local area, which is deservedly higher than R_a. The land market equilibrium requires that land rents, $r(x)$, to satisfy equation (25):

$$r(x) = \max\{r_f^*(x), r_h^*(x), R_a\}, \tag{25}$$

where the rent at the city edge is equal to the agricultural land rent, R_a.

We assume that the remaining sectors other than households and firms occupy a fixed share of land in each location of the city (θ_t). The proportions of the rest of the land at each location x that are allocated to firms and households are determined by their bidding prices, as shown in equation (26) and equation (27), respectively.

$$\theta_f^*(x) = \begin{cases} 1-\theta_t, r_f(x) > r_h(x) \; and \; r_f(x) \geq R_a \\ 0.5*(1-\theta_t), r_f(x) = r_h(x) \; and \; r_f(x) \geq R_a \\ 0, r_f(x) < r_h(x) \; or \; r_f(x) < R_a \end{cases}, \tag{26}$$

$$\theta_h^*(x) = \begin{cases} 1-\theta_f^*(x)-\theta_t, r_h(x) \geq R_a \\ 0, r_f(x) < R_a \end{cases}. \tag{27}$$

Then, the aggregate revenue of land rents for the whole city y_{rent} can be obtained by using equation (28):

$$y_{rent} = \sum_{i=1}^{L} 2\pi x_i [\, \theta_f^*(x_i)(r_f^*(x_i) - R_a) + \theta_h^*(x_i)(r_h^*(x_i) - R_a)] * \Delta x. \qquad (28)$$

3.4.2. Labor market

Given that the city is assumed to be a closed-form system with a fixed number of households, *N*, the condition for labor market clearing requires that the supply of labor equals the demand of labor:

$$\sum_{i=1}^{L} 2\pi x_i \frac{\theta_h^*(x_i) * \Delta x}{q^*(x_i)} = \sum_{i=1}^{L} 2\pi x_i \theta_f^*(x_i) * \Delta x * d^*\,(x_i) = N. \qquad (29)$$

It is assumed that only after all jobs in a ring are filled, the remaining workers living in this ring would consider commuting to another ring for employment. As such, at equilibrium, the commute demand of each ring can be expressed as:

$$D(x) = \left(\frac{\theta_h^*(x)}{q^*(x)} - \theta_f^*(x) \cdot d^*\,(x)\right) \cdot \Delta x \cdot 2\pi x. \qquad (30)$$

3.5 The solution of equilibrium model

There are 16 unknown variables in the land use equilibrium model, which requires 16 equations for the solution, including equations (3), (4), (6)-(9), (12), (14)-(16) and (25)-(30). To solve the 16 formulas, with the aid of the nested fixed-point algorithm used by Zhang and Kockelman (2016a), we develop a new iterative algorithm, shown as follows. Following Anas (2020), the equilibrium value is obtained by cycling between the two sub-models until they converge.

A. Set initial values of $\theta_f^0, F^0, w^0(x_c), u_0, TC_0, y_{rent}^0, x_L$. Assign the value of $\sigma, \zeta, \eta, \gamma, \kappa, R_a, \theta_t$ and N. Define travelers' risk/ambiguity attitudes and taste preference parameters based on Li et al. (2022)'s empirical estimation.

    a. Let $F = F^0, y_{rent} = y_{rent}^0$, $w(x_c) = w^0(x_c), \bar{u} = \bar{u}_0, \theta_f = \theta_f^0$, calculate $\{w(x)\}$ which satisfies $w(x_{i+1}) = w(x_c) + TC(x_{i+1})$, and compute $y(x)$ by equation (3). $TC(x_{i+1})$ is the annual travel cost from x_{i+1} to the employment center.

    b. Calculate $q(x)$ by equation (7). Compute the city population by the first part of equation (29). If $|\sum_{i=1}^{L} 2\pi x_i \frac{\theta_h^*(x_i)*\Delta x}{q^*(x_i)} - N| < e_{N1}$, where e_{N1} is a minimal value, returns $w^*(x) = w(x)$ and then goes to Step c. If

$\sum_{i=1}^{L} 2\pi x_i \frac{\theta_h^*(x_i)*\Delta x}{q^*(x_i)} - N > 0$, $w(x_c) = w(x_c) - 1$; If $\sum_{i=1}^{L} 2\pi x_i \frac{\theta_h^*(x_i)*\Delta x}{q^*(x_i)} - N \leq 0$, $w(x_c) = w(x_c) + 1$. Repeat Steps a-b until the convergence condition is satisfied.

c. With $\{w^*\}$, calculate $d(x)$ by equation (14).

d. Compute the city population by the second part of equation (29). If $|\sum_{i=1}^{L} 2\pi x_i \theta_f(x_i) * \Delta x * d\ (x_i) - N| < e_{N2}$, where e_{N2} is a minimal value, returns $u^* = u_0$ and then goes to Step e; If $\sum_{i=1}^{L} 2\pi x_i \theta_f(x_i) * \Delta x * d\ (x_i) - N > 0, u = u + 1$. If $\sum_{i=1}^{L} 2\pi x_i \theta_f(x_i) * \Delta x * d\ (x_i) - N \leq 0, u = u - 1$.Let $w(x_c) = w^0(x_c)$ and go back to Step a and recalculate the value of $\{w\}$.

e. With $\{w^*, u^*\}$, compute r_f, r_h, y_{rent} by equations (15), (9) and (28), respectively. If $|y_{rent} - y_{rent}^0| < e_{rent}$, where e_{rent} is a minimal value, return $y_{rent}^* = y_{rent}$, and go to Step f. Otherwise, replace y_{rent}^0 with y_{rent}, recompute y by equation (3) and then go back to Step a.

f. With the equilibrium functions $\{w^*, u^*, y_{rent}^*\}$, calculate θ_f and F with function (26) and (12), respectively. If $|F - F^0| < e_F, |\theta_f - \theta_f^0| < e_\theta$, where e_F and e_θ are minimal values, returns F^* and θ_f^*, and goes to B. Otherwise, replaces F^0 and θ_f^0 with F and θ_f, respectively, and then goes back to Step a.

B. Given the distribution of land use estimated from step A, calculate the commuting costs around the city as follows.

a. Calculate $\{D(x)\}$ by equation (30).

b. Assume that all arterial roads link the city center to the city edge and equally share the total road traffic of the city. Thus, the traffic situation on any one of the roads represents that of the whole city. We discuss one arterial road with n commuters under the closed system, and its travel demand matrix is given in equation (31):

$$D_{road}(x) = D(x) * \frac{n}{N}. \tag{31}$$

c. Given $D_{road}(x)$, estimate monetary cost $tc(x)$ based on the actual fuel consumption situation, and calculate commuter's perceived travel time $t^e(x)$ with functions (21).

d. Use functions (17)-(19) to calculate the probability of using each mode

$P_{car}(x)$, $P_{bus}(x)$ and $P_{rail}(x)$.

e. Estimate the travel costs of the city $\{TC(x)\}$ during the studied period at equilibrium by equation (16).

C. Given the kth circulation. If $\forall i \epsilon [1, L]$, $|D^k(x_i) - D^{k-1}(x_i)| < e_D$, where e_D is a minimal value, the algorithm stops. Otherwise, repeat A-C.

4. Model application

4.1 Simulation settings and data source

The LUTI model introduced in Section 3 is applied to Hobart, Tasmania (see Figure 3), to simulate the interaction between its commuters' mode choices under uncertainty and urban land use in the year of 2021. As bus and car are the available travel modes in the case study, the mode choice model in the transport system reduces to a binary choice mode without rail. The city-level parameters used in the land use model are sourced from the Australian Bureau of Statistics (2021) and summarized in Table 2. Assuming that all of the commuters behave as the rules presented in Section 3.3, we use the behavioral parameters estimated by Li et al. (2022) in this study (see Table 3). $\theta > 1$ implies that, in this type of loss domain with possible travel time outcomes, they would exhibit stronger ambiguity seeking towards the bus mode relative to the car mode. Commuters' risk attitudes are jointly determined by the values α and ψ, and the values of the two variables suggest the commuters exhibit risk seeking for medium/high-probability losses and risk aversion for low-probability losses.

Figure 3: The map of Hobart, Tasmania

Table 2: The parameter values used in the urban land use model

σ	ζ	η	γ	κ	R_a	N	x_L	θ_t	n
22,000	4	0.88	0.12	0.92	299,360 AUD/mile²	111,710	12.5 miles	0.3	7,447

Table 3: Commuters' behavioral parameters in the context of mode choice, sourced from Li et al. (2022)

α	ψ	θ	β_c	β_t
0.672	0.471	1.361	-0.219	-0.807

We focus on a representative road directly connecting the city center to the city edge, which accounts for one-fifteenth of the total traffic volume of Hobart. After dividing the road into 25 segments, the average travel time of a car running on each road segment is estimated with the Bureau of Public Roads (BPR) function:

$$t_{car}^{mean} = t_{free}(1 + a(\frac{Q}{Z})^b), \tag{32}$$

where t_{free} is the free-flow travel time; Q is the actual traffic volume of the segment; Z is the road capacity; a and b are parameters capturing the route-specific features of the traffic flow, taking the values of 0.15 and 4, respectively. The total travel time of a bus trip is calculated by equation (33):

$$t_{bus}^{mean} = t_{bus}^{IV} + t_{bus}^{wait} + t_{bus}^{walk}, \tag{33}$$

where t_{bus}^{IV} is the in-vehicle time; t_{bus}^{wait} is the waiting time or headway; t_{bus}^{walk} is the access/egress time from/to the workplace/home. The estimated in-vehicle time of a bus trip is the same as that of car (equation (32)). Walking time (equation (34)) and waiting time (equation (35)) are additional time components.

$$t_{bus}^{walk} = \frac{dw^{min} + (dw^{max} - dw^{min}) * \frac{x}{x_L}}{v_{walk}}, \tag{34}$$

where v_{walk} is walking speed, assuming 3.1 miles per hour in this study; x is the distance between a commuter's home and the CBD, x_L is the total length of the road, dw^{min} and dw^{max} are the minimum value and maximum value of the total walking distance from home to bus station plus the distance from bus station to workplace, which are assigned to 0.37 miles and 2.49 miles, respectively. Referring to the distribution of Hobart urban zones for PT services, t_{bus}^{wait} is set as:

$$t_{bus}^{wait} = \begin{cases} 5 \text{ minutes}, 0 \text{ miles} < x \leq 3.73 \text{ miles} \\ 10 \text{ minutes}, 3.73\text{miles} < x \leq 9.94\text{miles}. \\ 20 \text{ minutes}, x > 9.94\text{miles} \end{cases} \tag{35}$$

According to the real settings in Hobart, the bus fare is estimated by function (36):

$$f_{bus} = \begin{cases} 5.24 \text{ AUD}, 0 \text{ miles} < x \leq 3.73 \text{ miles} \\ 7.18 \text{ AUD}, 3.73 \text{ miles} < x \leq 9.94 \text{ miles}, \\ 10.78 \text{ AUD}, x > 9.94 \text{ miles} \end{cases} \tag{36}$$

The monetary cost of a single trip by car can be calculated by equation (37):

$$f_{car} = f_{car}^{fuel} * x + f_{car}^{fix} / Day/2, \tag{37}$$

where f_{car}^{fuel} is the fuel cost, and based on the average car fuel economy and gasoline price, it is calculated to be 0.36 AUD/mile; f_{car}^{fix} is the remaining car expenditures such as parking costs, annual registration fees and maintenance fees, which is assumed to be 6,000 AUD per annum[1]. Given the existence of travel time variability, each trip, either by bus or car, has three possible outcomes ($K = 3$): the shortest time, the normal time, and the longest time. According to the survey results in Li et al. (2022), the deviation ratio between the normal travel time and the other two possible outcomes $\left(\frac{t^{shortest} - t^{mean}}{t^{mean}}, \frac{t^{longest} - t^{mean}}{t^{mean}}\right)$ with their corresponding probabilities are given in Table 4.

[1] See this website for the cost components of owning a car in Australia: https://www.savvy.com.au/the-cost-of-owning-a-car-in-australia/

Table 4: The travel time distributions: Baseline model

	Car	Bus
The deviation ratio between the normal travel time and the shortest travel time	-21.22%	-15.32%
The deviation ratio between the normal travel time and the longest travel time	+34.08%	+34.39%
Likelihood of experiencing the shortest time	0.438	0.407
Likelihood of experiencing the normal time	0.288	0.286
Likelihood of experiencing the longest time	0.274	0.307

4.2 Simulation results

4.2.1 Baseline model

Table 5 presents the simulation results of the baseline model under the real settings of Hobart. The simulation results reveal that enterprises are located close to the city center (within a radius of 1.5 miles); while residential areas are mainly located at 1.5-12 miles away from the city center. This finding is in line with Hobart's urban form, where the boundary between the enterprise cluster and residential areas is about 1.43 miles from the city center. The modal split, average income and residential density estimated from the baseline model are also close to the available market evidence.

Table 5: Baseline model outputs vs. Hobart's market evidence

	Baseline model	Market evidence
Radius of the CBD (miles)	1.50	1.43[1]
Average income (AUD/person/year)	56,809.68	54,937.08[2]
Annual rent income (million AUD/year)	1,109.83	-
Average commuting cost (AUD/person/year)	7,124.28	-
Annual car commuting distance (million miles/year)	399.18	-
Average commuting distance of a single trip (miles/person)	7.72	-
Average car modal share	92.74%	92.57%[2]
Average bus modal share	7.26%	7.43%[2]
Average annual bid-rent of firms at the CBD (million AUD/mile^2)	146.73	-
Average annual bid-rent of residents in the residential area (million AUD/square mile/year)	2.36	-
Average job density at the CBD (jobs/square mile)	36,775.86	-
Average residential density in the residential area (persons/square mile)	346.57	324.0[3]
Average agglomeration at the CBD	34,250.32	-

Notes:

[1]Sourced from a map made by the Australian Bureau of Statistics: https://absstats.maps.arcgis.com/apps/MapSeries/index.html?appid=7fe915ad339041a8a79d1e07392c7d54.

[2]Sourced from the Australian Bureau of Statistics: https://www.abs.gov.au/census/find-census-

data/quickstats/2021/601.

[3]Sourced from https://worldpopulationreview.com/world-cities/hobart-population.

4.2.2 What if travel time reliability is improved?

Emerging technologies such as automated vehicles are expected to reduce road accidents, improve the stability of traffic flow and better coordinate vehicles, consequently leading to a more efficient and reliable transport network (Gokasar et al., 2023; Yu et al. 2021).[2] This subsection investigates how the potential improvement of travel time reliability (relative to the baseline setting shown in Table 4) might affect travel behavior and land use. Two scenarios are designed (see Table 6), holding all other factors constant. In Scenario 1, traveling by car and bus has an equal probability of on-time arrival being 70%; while Scenario 2 assumes a higher chance of arriving earlier when commuting by bus, in addition to improved reliability for both modes.

Table 6: Improved travel time reliability scenarios

	Scenario 1		Scenario 2	
	Car	Bus	Car	Bus
The deviation ratio between the normal travel time and the shortest travel time	-15.0%	-10.0%	-15.0%	-25.0%
The deviation ratio between the normal travel time and the longest travel time	+30.0%	+30.0%	+30.0%	+15.0%
Likelihood of experiencing the shortest time	0.15	0.15	0.15	0.40
Likelihood of experiencing the normal time	0.70	0.70	0.70	0.50
Likelihood of experiencing the longest time	0.15	0.15	0.15	0.10

Table 7 presents the key outputs under the two scenarios and their percentage changes relative to the baseline model ($\frac{x_{scenario}-x_{baseline}}{x_{baseline}}$). As shown in Table 7, both scenarios would lead to a shift towards a more sustainable transport system in terms of reductions in commuting cost, distance and car modal split. It is rather encouraging that the annual car commuting distance drops substantially by 7.90% (Scenario 1) or 11.09% (Scenario 2), attributed to (a) the shorter average commuting distance per trip and (b) the increased bus modal share. In addition to a larger CBD, the average residential density in the suburbs increases, as commuting becomes less costly and workers can choose residences farther from the city center in locations where housing is more affordable. A consequence is that the annual rent income falls. These findings exhibit the role of enhanced reliability and reduced commuting costs in facilitating city growth (Moore et

[2] While we cannot pinpoint the improvement in travel time reliability due to each of these technological developments, it is reasonable to assume that they will support it in general.

al., 2020; Takayama et al., 2020).

Table 7: Scenario outcomes and their changes relative to the baseline model outputs

	Scenario 1		Scenario 2	
	Value	Percentage changes	Value	Percentage changes
Radius of the CBD (miles)	2.5	+66.67%	3.0	+100.00%
Average income (AUD/person/year)	54,599.69	-3.89%	53,799.23	-5.30%
Annual rent income (million AUD/year)	1,062.68	-4.25%	1,044.05	-5.93%
Average commuting cost (AUD/person/year)	6,945.42	-2.51%	6,871.51	-3.55%
Annual car commuting distance (million miles/year)	367.65	-7.90%	354.91	-11.09%
Average commuting distance of a single trip (miles/person)	7.39	-4.27%	7.24	-6.22%
Average car modal share	89.56%	-3.43%	88.17%	-4.93%
Average bus modal share	10.44%	+43.80%	11.83%	+62.95%
Average annual bid-rent of firms at the CBD (million AUD/mile^2)	39.21	-73.28%	25.83	-82.39%
Average annual bid-rent of households at residential area (million AUD/mile^2/year)	2.33	-1.11%	2.36	-0.06%
Average job density at the CBD (jobs/mile^2)	10,178.05	-72.32%	6,796.63	-81.52%
Average residential density in the residential area (persons/mile^2)	357.45	+3.14%	365.09	+5.34%
Average agglomeration at the CBD	11,089.85	-67.62%	7,556.87	-77.94%

We also investigate the spatial distributions of traffic and land use patterns. Figure 4 shows that, under the two scenarios, improved travel time reliability stimulates the demand for properties in the suburbs (Figure 4a). Meanwhile, additional employment areas would be created away from the city center. Influenced by the overall lower job density (Figure 4b), the agglomeration (Figure 4c) and average bid-rent of firms (Figure 4d) would decline, and the flattening bid-rent gradients also reflect higher demand for low density and lower demand for urban amenities (Delventhal et al., 2022). The bid-rent of firms (Figure 4d) and residents (Figure 4e) co-varies with the job density (Figure 4b) and residential density (Figure 4a), respectively. These findings are consistent with relevant studies (Liu et al., 2021; Larson & Zhao, 2020; Gelauff et al., 2019).

A key finding is that urban expansion can be accompanied with sustainable travel behaviors through reliability improvement (see Figure 5 and Figure 6). However, many previous studies argued that urban expansion may lead to higher travel costs and even traffic congestion due to the intensified use of private cars (Nechyba & Walsh, 2004; Gelauff et al., 2019); while this conclusion is typically drawn without the explicit consideration of travel time reliability improvement (Lu et al., 2021; Zhao, 2020; Bhatta, 2010). Our finding implies that reliability improvement makes the bus mode more attractive to the commuters than the car mode. This is primarily attributed to the aggregated role of ambiguity seeking in promoting entry (Gutierrez et al., 2020), which results in a more positive attitude toward the former source of uncertainty, and reflects a higher willingness to accept (WTA) value for the unknown probability distribution embedded in the bus mode. Moreover, the empirical parameters (ψ and θ) that characterize their decision rules under uncertainty suggest that commuters would pay greater attention to the best/worst outcomes (see Li et al., 2022 for details). Psychologically, this behavioral trait reinforces the perceived gains of conquering the major drawback of bus (late arrival), where the likelihood of the worst travel outcome is assumed to reduce from 0.307 (baseline) to 0.15 (Scenario 1) and 0.10 (Scenario 2). The enhanced attractiveness through reliability improvement, along with commuters' ambiguity-seeking behaviors, stimulates the bus modal share (see Table 7), and reduces car usage (Figure 5) and dependence (Figure 6). As such, traffic congestion can be mitigated, resulting in increased average travel speed and improved travel time reliability. Considering Hobart's low population/job density and high car dependency coupled with limited PT, these improvements allow its residents to travel farther and more efficiently.

Moreover, the simulated spatial distributions (Figure 4a & Figure 4b) suggest that there is a tendency for employers and employees to co-locate away from the city center in ways that can reduce the costs of interacting with each other, incentivized by a more reliable transport network. For example, firms and employees may be attracted to locations with strong but unobserved productivity advantages (Duranton & Puga, 2020). This tendency can be inferred as the reduced distance per commuting trip (see Table 7), which mitigates negative externalities such as congestion. With such co-location, urban expansion can be regarded as a solution for smaller cities to grow, instead of the problem (Gordon & Richardson, 2012). Firms can also take advantage of enhanced reliability and mobility, and re-engineer their supply chains so as to serve their partners and customers in a more efficient manner, by using, for example, just-in-time inventory control and quick response. Logistics costs such as delays and lead times can be lowered, as a greater proportion of road capacity can be allocated to freight vehicles due to less car usage. Meanwhile, commuters can enjoy substantial gains including lower travel costs, better access to jobs, better dwellings, and higher productivity (as on-time arrival becomes more likely). As such, the cost efficiency of firms and residents can be improved, if they decentralize in a way simulated in this study.

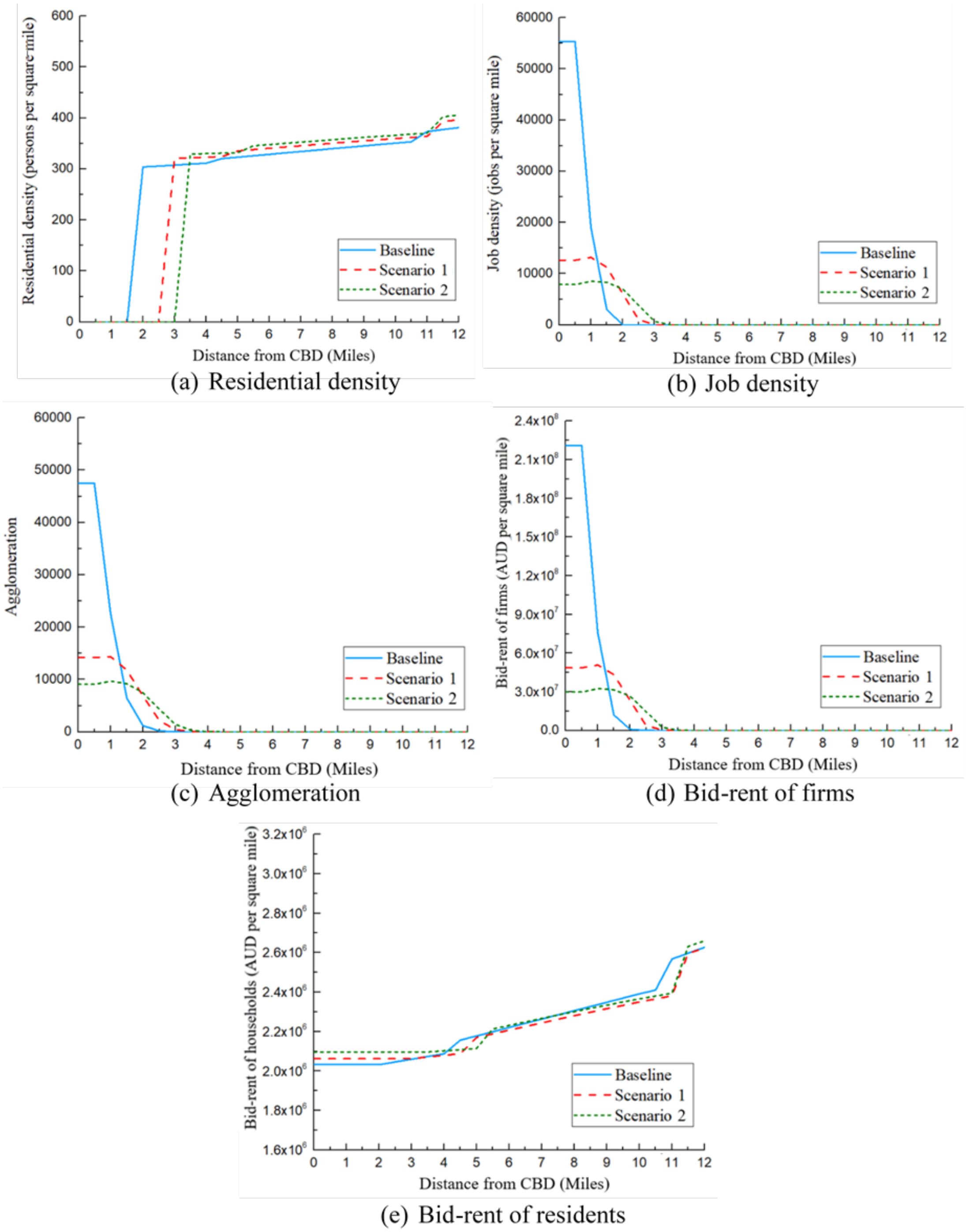

Figure 4: Spatial distributions of land use under different scenarios

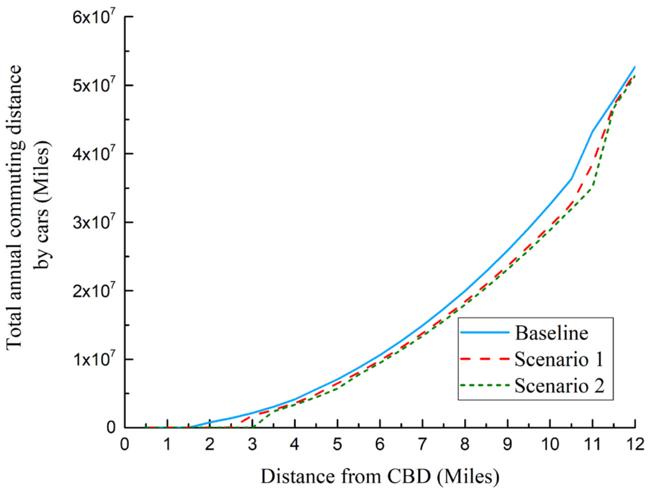

Figure 5: Spatial distributions of annual car commuting distance under different scenarios

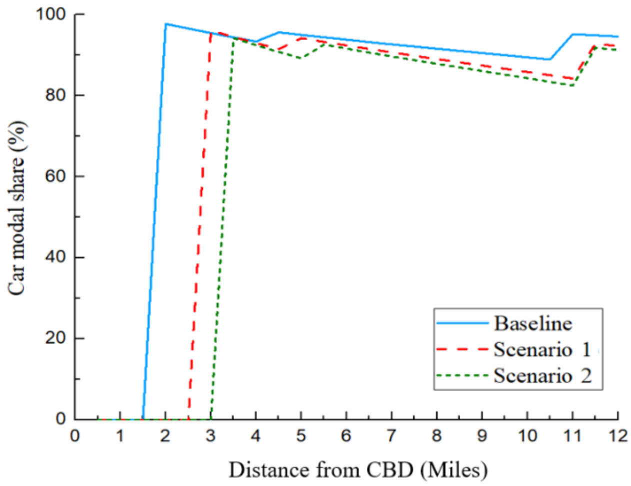

Figure 6: Spatial distributions of car modal share under different scenarios

5. Conclusions

In this paper, we have incorporated commuters' mode choices in the presence of travel time variability into LUTI modeling, while accounting for the complexities in them. Using a conceptually appealing and tractable way to quantify the role of travel time variability, this study has demonstrated how and to what extent an important behavioral mechanism, namely ambiguity attitude, can be aggregated into an additional impact on traffic patterns and urban form. In doing so, we have introduced a revised travel cost function, endogenously determined by commuters' uncertain mode choices depending on an extended list of behavioral mechanisms from both economic and psychological perspectives. We then used it to connect the transport sub-model to the land use sub-model. The improved behavioral realism is valuable for understanding the implications of their interactions so as to improve the credibility of LUTI simulation. In particular, our model accounts for the positive role of ambiguity seeking in encouraging commuters' likelihood of using bus, and the baseline model results are consistent with the market evidence. Travel time reliability has a direct effect on the level of accessibility, which reflects a joint quality of the land use and transport systems. The scenario analysis shows that the improvement of travel time reliability would lead to a smart development in terms of sustainable travel and city growth. Another interesting finding is that the average commuting distance would reduce as travel time reliability improves, and there is a co-location mechanism for employers and employees to mitigate costs and externalities and to improve accessibility and efficiency. Under the smart urban development, as simulated in this study, the changing travel behaviors and land use patterns can lead to substantial gains for individuals and the society.

In ongoing research, we will extend the model by including land-use regulations and economic development strategies. We will also consider the impacts of technology developments in more detail in the next step of research, such as the associations between the penetration and level of automation of connected and autonomous vehicles (CAVs) and the urban network's reliability. Finally, the current model did not consider the impact of working from home (WFH) and virtual accessibility, which can impact travel behavior and land use (Delventhal et al., 2022; Mouratidis et al., 2021).

Credit author statement

Zheng Li: Conceptualization, Methodology, Investigation, Writing-Original draft preparation, Writing - Review & Editing, Supervision; **Jingjing Zeng:** Methodology, Software, Formal analysis, Writing- Original draft preparation; **David A. Hensher:** Methodology, Writing - Review & Editing; **Chenyang Wu**: Writing - Review & Editing.

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