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*Research Article*

# Economic and Environmental Effects of Public Transport Subsidy Policies: a Spatial CGE Model of Beijing

**Ping Xu**,[1] **Weiyu Wang**,[2] **and Chunxia Wei**[1]

[1] *School of Economics, Beijing Technology and Business University, Beijing 100048, China*
[2] *Tax Institute of State Administration of Taxation, Yangzhou 225007, China*

Correspondence should be addressed to Ping Xu; xuping@th.btbu.edu.cn

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Public transport plays an important role in the environment. This study established a Spatial Computable General Equilibrium (SCGE) model to examine the economic and environmental effects of public transport subsidy policies. The model includes firms, consumers, and traffic modules in one framework. Statistical data from Beijing were used in calibration to obtain benchmark equilibrium. Based on the equilibrium, simulations compared citywide social welfare, jobs-housing spatial population distribution, and environmental outputs under four subsidy policies: fare subsidy, cash grants, road expansion, and public transport speedup. Based on the results regarding the effects of public transport policies, conclusions can be drawn about which policies will have greater overall social influence and should therefore be used.

## 1. Introduction

Public transport has acquired increasing significance in urban residential life, and governments all over the world provide different forms of transport-related subsidies. In 2005, for example, transport subsidies in the EU reached 270 billion euros, of which about 50% was utilized for road infrastructure construction. In 20 public transport systems in the United States, subway fare subsidies accounted for 29%–89% of operating costs, while bus fare subsidies accounted for as much as 57%–89% [1]. The case is similar in Beijing, China, where cumulative bus subsidies reached 122.5 billion in 2015, following the low-fare policy initiated in 2007. The economic and environmental effects of public transport subsidies are controversial topics among sociologists and policymakers.

The main purpose of public transport subsidy policies is to provide transit services to citizens. As such, studies have focused on the transit quality issue from various dimensions. Hensher, Stopher, and Bullock [2] investigated ways to quantify service quality and compare levels within and between bus operators. Eboli and Mazzulla [3] proposed a methodology for measuring transit service quality based on the use of both passenger perceptions and transit agency performance measures. Hassan, Hawas, and Ahmed [4] combined subjective and objective measures to assess service quality. These studies have laid a solid theoretical foundation for the evaluation and development of public transport systems. Although measuring efficiency and effectiveness of transit services is very important, those studies did not consider the social effects of subsidy policies or reveal the subsidies' mechanisms of action.

Given the influence of subsidies on transport costs and travel times, some studies have investigated those effects from the perspective of social welfare. There are two noteworthy yet contrasting theories that either support subsidy policies or suggest canceling them.

Based on the Mohring effect [5], Jara-díaz and Gschwender [6] acknowledged that government subsidies can guarantee adequate public transport services at fair prices. Santos, Behrendt, and Maconi et al. [7] suggested that if the use of private cars could not be charged at calculated full social costs, the suboptimal option would be to reduce public transport prices to enhance its substitutability for private cars. In a general model-based study, Parry and Small [1] found that related social welfare will still improve, even if a subsidy exceeds two-thirds of the total operating costs.

Other scholars, however, believe the effects of subsidies are limited and negligible. Hensher [8] argued that lowering service fares with subsidy support provided no significant improvement in the public transport split rate. Proost and Dender [9] argued that even if rush hour fares were fully subsidized, the rise in social welfare would be limited. Savage [10], moreover, suggested that subsidies could create inefficiencies in public transport companies since their management costs would increase faster with government subsidies. All of the abovementioned research has focused mainly on traffic, travel costs, and resident welfare. However, it has overlooked the effects of subsidies on residents' work-leisure choices and on population distribution.

Some studies have focused on the effects of subsidies on labor supply. Richter [11], for example, argued that subsidizing commuter traffic would be equivalent to taxing leisure and would thus stimulate labor supply. Borger and Wuyts [12] suggested that public transport subsidies could reduce the car travel demand, parking cost, and congestion issues as an embodiment of positive externalities. Dender [13] argued that subsidizing commuter trips would bring about significant efficiency improvements. Basso et al. [14, 15] compared the efficiency and substitutability of three different policies. These researches, however, only considered effects on the labor market without considering the effect of subsidies on consumers' choices for job-housing locations.

By introducing the concept of "space" into the research framework, the function of subsidies can be studied based on their action mechanisms in the spatial distribution of populations. The classical monocentric urban model assumes that transport subsidies will decrease the bid-rent curve slope, resulting in a larger urban area, lower population density, and a reduced suburban-urban rent differentiation, though they will cause urban expansion and road congestion [16, 17]. In light of such negative effects, Borck and Wrede [18], adopting the perspective of political economy, considered the political ramifications of government decisions to subsidize public transport as a form of income redistribution. In contrast, the multicenter urban model argues that transport subsidies can optimize the allocation of labor if there are wage differences, agglomerative economies, or job-housing spatial imbalances between zones. Martin [19] suggested that subsidies could gradually reduce the job-housing imbalance among low-income groups. Accordingly, Zenou [20] noted that different subsidies had varied effects on alleviating the job-housing imbalance among low-income groups. Borck and Wrede [21] argued that transport subsidies could reduce the distortions of residents' employment decisions caused by payroll taxes and internalize the externality of the employment area, resulting in more efficient labor allocation. The abovementioned studies considered both the labor market and job-housing location choices. Despite taking into account the spatial effects of subsidies, labor supply was usually considered as an exogenous variable for the convenience of calculation, regardless of the interactions between subsidies and "work-leisure" policies, consumption, or other factors.

Recently, a growing body of literature has assessed the environmental effects or external costs of transit. Ayyildiz et al. [22] compared fuel consumption and carbon emissions in terms of driving styles before and after eco-driving training. Tong et al. [23] estimated the life-cycle ownership costs for buses and infrastructure as well as the environmental externalities of greenhouse gases and air pollutants emitted during the life cycle of buses powered by alternative fuels. These studies have shown that environmental effects are significant and should not be ignored when considering transport effects.

Subsidies have been shown to have prominent effects on social welfare, labor markets, and population distribution in diversified mechanisms. However, most previous studies have focused on such effects in terms of individual aspects as opposed to combining several different outputs into one analysis framework. Excising subsidies-involved variables from the resulting effects and neglecting the mechanisms of interactions can give rise to unilateralism in research results. Although computable general equilibrium (CGE) has been widely used in many studies, gradually becoming a mainstream approach for policy analysis models, only Tschaaktschiew and Hirte [24] have investigated transport subsidies using a CGE framework model—specifically, a spatial CGE model that considered "spatial" decisions. In addition, there have not been sufficient comparative studies of different levels and forms of subsidies, especially in terms of quantitative effects, all of which have practical significance for policymakers. Therefore, it is necessary to incorporate the effects of public transport subsidies on social welfare, labor markets, and the environment, as well as the mechanisms of various subsidies, into a framework system for further survey and discussion.

To investigate these practical problems, taking Anas and Xu [25] and Tschaaktschiew and Hirte [24] as the basis, this study constructed a SCGE model integrating traffic, social welfare, job-housing spatial choice, $CO_2$ emissions, and other factors into a framework based on the rudimentary theory of traffic and spatial economics. The goal of this discussion is to explain and analyze the comprehensive effects of public transport subsidies on city development, provide guidelines for improving subsidy policies, and deliver more efficient services to communities. The rest of this paper is organized as follows. Section 2 builds the public transport subsidy SCGE model. Section 3 describes the parameter calibration using data of Beijing and benchmark equilibrium. Section 4 explains the scenario design of the policies and presents simulation results and analysis. Section 5 concludes the paper and gives suggestions.

## 2. SCGE Model of Public Transport Subsidy

Assume that, in a typical circular city, a wedge-shaped city area with incision angle $\varphi$ is studied, and the entire area is divided into I=9 distinct zones, as shown in Figure 1. Among these nine zones, the central zone, where $i$=5 is assigned as downtown, has a diameter of $d_i$, and the rest of the zones share a width of $d_i$ as well.

As shown in Figure 1, zones 3–7 are urban areas, while zones 1, 2, 8, and 9 are suburban areas. Therefore, the downtown area is $1/2d_i^2\pi\varphi$, and the area of the remaining

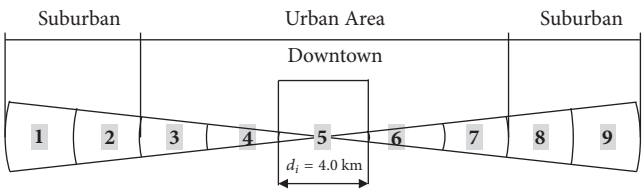


Figure 1: Structure of a wedge-shaped city.

zones $i$ can be represented as $A_i = \varphi\pi(R_i^2 - R_{i-1}^2)$, where $R_{i-1}$ and $R_i$ are the inner and outer radiuses, respectively, for a certain zone. This assumption complies with the fact that the larger the distance between a zone and downtown, the more adequate the land supplies, which facilitates the model computation of travel distances.

*2.1. Firms Module.* It is assumed that firm production activities are distributed in all zones and that each zone produces only one kind of composite product exclusively. Land and labor markets are perfectly competitive markets. For zone $i$, the land market, labor market, and product market will clear in the zone, resulting in equilibrium rent $r_i$, wage $w_i$, and product price $p_i$. The Cobb-Douglas function is used as the production function. Further, only two types of inputs are discussed here—land and labor—without considering the number of firms. The aggregate output of zone $i$ is $X_i$; $M_i$ and $Q_i$ stand for the amount of labor input and land input in the zone, respectively. Then, the production equation of firms is

$$X_i = BM_i^{\delta}Q_i^{\mu} \quad \delta + \mu = 1, \tag{1}$$

where $B$ is the efficiency coefficient and $\delta$ and $\mu$ are the output elasticities of labor and land. To obtain the maximal profit for firms, the conditional input demand functions are

$$\begin{aligned} M_i^* &= \delta p_i X_i w_i^{-1} \text{ and} \\ Q_i^* &= \mu p_i X_i r_i^{-1}, \end{aligned} \tag{2}$$

and the cost function is

$$\mathrm{C}(w_i, r_i, X_i) = \left(B\delta^{\delta}\mu^{\mu}\right)^{-1} w_i^{\delta} r_i^{\mu} X_i \tag{3}$$

Free entry in each zone for all firms leads to equivalence in product equilibrium price and its marginal cost, which gives

$$p_i = \left[B\delta^{\delta}(1-\delta)^{1-\delta}\right]^{-1} w_i^{\delta} r_i^{1-\delta}. \tag{4}$$

*2.2. Consumer Module.* Assume there are $N$ consumers in the city. A consumer resides in some zone $i$, works in some zone $j$, and shops in some zone $k$. Thus, the consumer's work-home one-way commute distance is $d_{ij}$, and the one-way shopping travel distance is $d_{ik}$. Zone determination $(i, j)$ stands for the residence-job location choice for the customer, which is an endogenous variable. In reality, customers can purchase products from any zone. However, to simplify calculations, residents are limited to purchasing one unit of a single kind of good without considering "trip chain." Therefore, as for characteristic parameters under this limitation, the number of trips the consumer takes to zone $k$, represented by $Z_{ijk}$, is equal to the quantity of bought goods. Further, the lot size is $q_{ij}$, and leisure time is $L_{ij}$.

Under the income constraint, a consumer achieves utility maximization through buying composite products, making full use of the living space, and enjoying leisure time. Stochastic utility function $U_{ij}$ is introduced to describe the consumer's choice:

$$\begin{aligned} U_{ij} &= aln\left(\sum_{k=1}^{I} Z_{ijk}^{\eta}\right)^{1/\eta} + \beta lnq_{ij} + \gamma lnL_{ij} + u_{ij} \\ &\alpha, \beta, \gamma > 0,\ \alpha + \beta + \gamma = 1,\ 0 < \eta < 1. \end{aligned} \tag{5}$$

In this equation, the constant elasticity of substitution (CES) utility function is adopted as the subutility of purchase product $Z_{ijk}$, and the constant elasticity of substitution $1/(1-\eta)$ reflects the consumer's preference for shopping zones. When $\eta$ approaches 1, the utility function develops into a linear elasticity of substitution function where the consumer chooses to make purchases in zones with minimum full economic shopping cost. When $\eta$ approaches negative infinity, the utility function evolves into a complete complementary function where the consumer makes purchases based only on his or her demands, regardless of the full economic shopping costs.

In addition, the idiosyncratic taste constant $u_{ij}$ is a heterogeneous preference variable that depicts the features of varied consumers and their preference differences in residence-job spatial choices. As in many other studies [24, 25], it is hypothesized here that idiosyncratic tastes are independently and identically distributed for each location choice$(i, j)$—namely, without spatial correlation. After considering his or her own heterogeneous preference, the consumer will make decisions about the optimal residence-job location. Assuming $(i, j)$ pairs display a discrete distribution, the probability that a consumer chooses a specific $(i, j)$ pair to achieve maximum utility $U_{ij}^*$ is

$$\begin{aligned} \Psi_{ij} &= Prob\left[U_{ij}^* > U_{sm}, \forall (s,m) \neq (i,j)\right] \\ &= Prob\left[V_{ij} + u_{ij} > V_{sm} + u_{sm}, \forall (s,m) \neq (i,j)\right], \end{aligned} \tag{6}$$

where $\mathrm{V}_{ij}$ is the fixed utility partition. As discussed above, the i.i.d. $u_{ij}$'s are Gumbel distributed with expected value $\mathrm{E}[u_{ij}] = 0$, standard variance $\sigma^2$, and dispersion parameter $\lambda = \pi/(\sigma\sqrt{6})$. Therefore, the probability of the consumer choosing residence-job location $(i, j)$ can be described with a multinomial logit model:

$$\begin{aligned} \Psi_{ij} &= \frac{\exp\left(\lambda V_{ij}\right)}{\sum_{s=1}^{I}\sum_{m=1}^{I}\exp\left(\lambda V_{sm}\right)} \\ \sum_{i=1}^{I}\sum_{j=1}^{I}\Psi_{ij} &= 1. \end{aligned} \tag{7}$$

Dispersion parameter $\lambda$ mirrors the preference heterogeneity of all consumers in the zones. When $\lambda \to \infty$,

consumer preferences demonstrate high-level homogeneity, and they tend to make identical decisions. In this case, the probability $\Psi_{ij}$, which corresponds to maximum utility $V_{ij}$, approaches 1, while other possibilities diminish. Meanwhile, when $\lambda \to 0$, $V_{ij}$, the systematic part of utility is masked with heterogeneity, meaning that consumers choose working and living zones randomly, and each $(i, j)$ pair's probability of being chosen is $\Psi_{ij} = 1/I^2$.

Changes in social welfare are measured by the Hicksian equivalent variation (EV>0 for a welfare-improving policy)—that is, the equivalent income transfer necessary to compensate a household in the prepolicy benchmark case in order to reach equality with the postpolicy utility level. Overall utility, in turn, is calculated as the expected value of maximized utilities. Based on the probability hypothesis mentioned above, the maximum utility is also in compliance with Gumbel distribution, which derives the expected value of the maximized utilities as

$$\mathrm{E}\left[\max_{ij}\left(V_{ij}+u_{ij}\right)\right] = \frac{1}{\lambda}\ln\sum_{s=1}^{I}\sum_{m=1}^{I}\exp\left(\lambda V_{sm}\right). \quad (8)$$

To maintain model conciseness and research focus, it is assumed that the city economy is closed. The number of work days in a year for a consumer is $D$, and $p_k$ stands for composite product price in zone $k$. $c_{ij}(tm, \Gamma_i)$ is the one-way commuting travel cost from residential zone $i$ to working zone $j$; $c_{ik}(tm, \Gamma_i)$ is the one-way shopping travel cost from zone $i$ to shopping zone $k$; $t_{ij}(tm, \Gamma_i)$ is the one-way commuting time from residential zone $i$ to working zone $j$; and $t_{ik}(tm, \Gamma_i)$ represents the one-way shopping travel time from zone $i$ shopping zone $k$. Travel cost $c_{i\xi}(tm, \Gamma_i)$ and travel time $t_{i\xi}(tm, \Gamma_i)$ are both determined by travel modes $tm$ and traffic condition $\Gamma_i$, where $\xi \in [j, k]$.

Excluding the bicycle, as it is a travel mode of less proportion, walking, private cars, and public transport are included as travel modes in the discussion—specifically, $tm \equiv \{walking, car, public\ transport\}$. $\Gamma_i$ represents the traffic congestion condition and is defined as the ratio of road traffic flow and road capacity: $\Gamma_i \equiv F_i/K_i$, in which $F_i$ is the double-sided traffic flow through zone $i$ every day, including commuting and shopping trips, and $K_i$ is the road area of zone $i$ (road capacity). $s^{tm}$ is the government subsidy ratio for travel mode $tm$, and $S$ represents the cash grant by the government. $M_{ij}$ is the labor hours supplied annually by the consumer. Then, the budget constraint of a consumer facing location choice $(i, j)$ is

$$\begin{aligned}\sum_{k=1}^{I} Z_{ijk}\left[p_k + 2c_{ik}\left(tm, \Gamma_i\right)\left(1 - s^{tm}\right)\right] + r_i q_{ij} \\ + 2\mathrm{D}c_{ij}\left(tm, \Gamma_i\right)\left(1 - s^{tm}\right) = w_j M_{ij} + S.\end{aligned} \quad (9)$$

The left side of (9) represents the consumer's total annual cost, including full shopping costs, housing expenses, and commuting costs. The full shopping cost comprises product price and travel cost after government subsidies. The right side of (9) is the disposable income of the consumer. In addition to budget constraints, the consumer is also subject to time constraints. $E$ represents the total annual time endowment, and $T_{ij}$ represents commuting and shopping travel time. Then, we have

$$M_{ij} + T_{ij} + L_{ij} = E, \text{ and} \quad (10)$$

$$T_{ij} = 2Dt_{ij}\left(tm, \Gamma_i\right) + \sum_{k=1}^{I} 2t_{ik}\left(tm, \Gamma_i\right) Z_{ijk}. \quad (11)$$

### 2.3. Transport Module

*2.3.1. Travel Cost.* The consumer's travel cost includes two parts: variable cost and fixed cost. $c^{1,tm}$ is the variable cost with travel mode $tm$, —namely, travel cost per km except for gasoline cost. Compared to walking and public transport, the variable travel cost of a private car includes gasoline cost, and $c^{2,car}$ is gasoline price per liter, while $g_{i\xi}^{car}$ is gas consumption for traveling from zone $i$ to zone $\xi$. $c^{3,tm}$ is the fixed cost with travel mode $tm$. Thus, one-way travel cost from zone $i$ to zone $\xi$ is

$$c_{i\xi}^{tm} = c^{1,tm} d_{i\xi} + c^{2,car} \times g_{i\xi}^{car} + c^{3,tm}. \quad (12)$$

In general, there is no congestion in walking and public transport (public transport in Beijing includes rail traffic and road traffic. Normally, there is no congestion in rail traffic. As a result of using dedicated bus lanes, there is only slight congestion in road traffic during the morning and evening rush hours). Under these two travel modes, $v^{tm}$ is the average speed with travel mode $tm$, which gives one-way travel time from zone $i$ to zone $\xi$ as $t_{i\xi}^{tm} = d_{i\xi}/v^{tm}$ in which $tm = \{walking, public\ transport\}$.

As for private car travel, travel speed and time depend on road congestion conditions. Adopting the commonly used BPR congestion function, a traveler spends an amount of time driving 1 km in zone $i$ by private car as follows:

$$t_i^{car}\left(F_i, K_i\right) = d_{i0}\left[1 + b\left(\frac{F_i}{K_i}\right)^c\right] \quad d_{i0}, b > 0,\ c \geq 1, \quad (13)$$

where $d_{i0} = 1/v_0$ is travel time by private car moving smoothly for 1 km in zone $i$ and $v_0$ is average speed without congestion. Larger values of $b$ and $c$ would result in exponential increments in estimated travel time.

Taking into consideration these three travel modes, and using $Pro_{i\xi}^{tm}$ to denote the probability of choosing a specific travel mode, travel cost and time from zone $i$ to $\xi$ will be

$$c_{i\xi}\left(tm, \Gamma_i\right) = \sum_{tm} Pro_{i\xi}^{tm} c_{i\xi}^{tm}, \text{ and} \quad (14)$$

$$t_{i\xi}\left(tm, \Gamma_i\right) = \sum_{tm} Pro_{i\xi}^{tm} t_{i\xi}^{tm}. \quad (15)$$

Travel mode choice probability $Pro_{i\xi}^{tm}$ is characterized using a multinomial logit model. $V_{i\xi}^{tm}$ is the fixed utility with travel mode $tm$. $l_1$ and $l_2$ outline the effect of travel cost and

time, respectively. $b^{tm}$ is a constant measuring other factors aside from travel time and cost.

$$Pro_{i\xi}^{tm} = \frac{\exp\left(V_{i\xi}^{tm}\right)}{\sum_{tm}\exp\left(V_{i\xi}^{tm}\right)}, \text{ and} \tag{16}$$

$$V_{i\xi}^{tm} = b^{tm} + l_1 c_{i\xi} + l_2 t_{i\xi}. \tag{17}$$

*2.3.2. Gas Consumption and $CO_2$ Emissions.* Traveling by private car engenders gasoline consumption and $CO_2$ emissions. Travel time, amount of gas consumption, and $CO_2$ emission are endogenous variables and are determined by travel speed. Thus, the amount of gas consumption when traveling 1 km in zone $i$ by private car is

$$g_i^{car}\left(F_i, K_i\right) = \frac{1}{740} e\left[e_0 + e_1\left(\frac{1}{t_i^{car}\left(F_i, K_i\right)}\right)^2 + e_2 t_i^{car}\left(F_i, K_i\right)\right], \tag{18}$$

where 1/740 is used to convert gasoline consumption in grams into liters, and $e_0 = 17.7766$, $e_1 = 0.0023606$, and $e_2 = 1461.87$ are constant parameters in the expression. $e$ is the efficiency coefficient for gas consumption calibration. Gas consumption leads to $CO_2$ emissions, and emissions in grams discharged by traveling 1 km by private car in zone $i$ are

$$em_i^{car}\left(F_i, K_i\right) = \frac{ef}{740} e\left[e_0 + e_1\left(\frac{1}{t_i^{car}\left(F_i, K_i\right)}\right)^2 + e_2 t_i^{car}\left(F_i, K_i\right)\right]. \tag{19}$$

In (19), $ef$ includes direct and indirect $CO_2$ emissions. The direct $CO_2$ emission and indirect emission for 1 liter of gasoline are 2340 g and 585 g $CO_2$, respectively. Therefore, both gasoline consumption and $CO_2$ emission depend on the travel speed of the private car $1/t_i^{car}(F_i, K_i)$, which is determined by traffic flow $F_i$ and road capacity $K_i$.

In addition, public transport inevitably generates $CO_2$ emissions, which can be represented by the average social $CO_2$ emission, $em^{public} = ASCE$. Hypothetically, public transport experiences no traffic congestion, and thus there is no difference in $CO_2$ emission levels among zones. Otherwise, for traffic flow $F_i$, the predicted commuting traffic flow from zone $i$ to zone $j$ is $F_{ij}^{w} \equiv N\Psi_{ij}$. Considering that no congestion occurs on weekends, for convenience, only shopping travel on working days is considered. Thus, the expected shopping travel per day from zone $i$ to zone $j$ is $F_{ij}^{s} \equiv (N/D)\sum_{\xi=1}^{I}\Psi_{i\xi}Z_{i\xi j}$, where $i$ is the residence zone, $\xi$ is the working zone, and $j$ is the shopping zone. Then, the total traveling traffic flow is

$$F_{ij} = F_{ij}^{w} + F_{ij}^{s}. \tag{20}$$

The travel time, gas consumption, and $CO_2$ emissions discussed above represent values corresponding to 1 km of travel in a specific zone. If travel crosses the boundaries of two or more zones, it is assumed that the travel distance in starting zone $i$, as well as in destination zone $j$, is equivalent to half the zone width. Setting the travel set in zone $i$ as $\Omega_i \equiv \{t_i^{car}, g_i^{car}, em_i^{car}\}$, travel set crossing from zone $i$ to zone $j$ is expressed as

$$\Omega_{ij} = \frac{1}{2}\left(d_i\Omega_i + d_j\Omega_j\right) + \sum_{\xi=i+1}^{j-1} d_\xi\Omega_\xi. \tag{21}$$

*2.4. Model Closure.* Combining all equations in the firm, consumer, and traffic modules, supply-demand equilibria are achieved for land, labor, and product markets. All land, labor, and product markets then result in clearing, characterized by the following equations:

Land market equilibrium:

$$\mathrm{N}\sum_{j=1}^{I}\Psi_{ij}^{*}q_{ij}^{*} + Q_i^{*} + K_i = A_i; \tag{22}$$

Labor market equilibrium:

$$\mathrm{N}\sum_{s=1}^{I}\Psi_{si}^{*}\left(E - T_{isi}^{*} - L_{si}^{*}\right) = M_i^{*}; \text{ and} \tag{23}$$

Product market equilibrium:

$$\mathrm{N}\sum_{n=1}^{I}\sum_{s=1}^{I}\Psi_{nsi}^{*}Z_{nsi}^{*} = X_i^{*}. \tag{24}$$

## 3. Parameters Calibration and Benchmark Equilibrium

Beijing is a representative city in China where public transport is subsidized. Here, its economics, population, and traffic-related statistics are used in calibration. The calibration commonly used to determine parameter values in CGE modeling ensures that the benchmark city found as a result of the basic simulation exhibits the economic figures, travel characteristics, and spatial patterns of a representative Beijing area. Data were mainly derived from the *Beijing Statistical Yearbook 2016* and *Beijing Traffic Development Annual Report 2016*. Certain parameters were derived from relevant domestic and international studies. Table 1 lists the calibrated values of the parameters in the SCGE model.

The fully circular city population is assumed to be 10.8 million, of which one-third is employed. That implies a population of 3.6 million commuters. Therefore, the total employed population is 100,000 in the 5° wedge-shaped city area. In the firm Cobb-Douglas production function, determinations of the function parameters $B$, $\delta$, and $\mu$ are attributed to Zhang et al. [26] and Wang and Ge [27] with slight adjustments. The utility function parameters $\alpha$, $\beta$, and $\gamma$ reflect the consumer's preference for shopping, housing, and leisure, respectively, and the values are set as 0.40, 0.17, and 0.43 to equilibrate the benchmark equilibrium values with the per capita consumption structure of Beijing data. The subutility function parameter of product purchasing is set as $\eta$=0.6, demonstrating that the substitutional elasticity

Table 1: Calibrated values of the parameters in SCGE.

| | | | | | |
|---|---|---|---|---|---|
| **City** | | | | | |
| Incision angle | $\varphi$=5° | | | | |
| Zone width | $d_i$=4 $km$ | | | | |
| **Firms** | | | | | |
| Production function | $B$=1.05 | $\delta$=0.65 | $\mu$=0.35 | | |
| **Consumers** | | | | | |
| Population | $N$=100 000 | | | | |
| Labor | $D$=250 d | $E$=4000 h/a | | $M_{ij}$=2000 h/a | |
| Utility function | $\alpha$=0.40 | $\beta$=0.17 | $\gamma$=0.43 | $\eta$=0.6 | |
| Dispersion parameter | $\lambda$=0.8 | | | | |
| **Travel** | | | | | |
| Travel modes ($tm$) | $v^{tm}$ | $b^{tm}$ | $c^{1,tm}$ | $c^{2,car}$ | $c^{3,tm}$ |
| Walking | 4 km/h | 6.20 | 0 | - | 0 |
| Private car | - | 7.41 | 0.3 | 6.2 | 0 |
| Public transport | 15 km/h | 7.16 | 0.2 | - | 1.5 |
| Fixed utility function | $l_1$=-0.1 | $l_2$=-0.3 | | | |
| **Transportation** | | | | | |
| | Zone 1(9) | Zone 2 (8) | Zone 3 (7) | Zone 4 (6) | Zone 5 |
| Road–land proportion | 0.05 | 0.075 | 0.09 | 0.12 | 0.40 |
| Travel time of private car $d_{i0}$ | 1/44 | 1/42 | 1/40 | 1/38 | 1/36 |
| BPR function parameters | b=6 | c=4 | | | |
| Gasoline consumption | e=1.26 | | | | |
| $CO_2$ emissions | ASCE=11.9 g/pkm | | | | |

for interzone products is $1/(1-\eta) = 2.5$. Assuming $D$=250 for a consumer's annual working days, the available time endowment is $E$=250∗16=4000 hours, and the annual labor supply is $M_{ij}$=250∗8=2000 hours according to an 8-hour work day.

The dispersion parameter $\lambda$=8.0 makes the employed population density in the benchmark equilibrium approximate to reality. Average walking speed is 4 km/h, and public transport speed is 15 km/h. In the travel mode choice function, parameters $b^{tm}$, $l_1$, and $l_2$, reflecting the traveler's preference, were chosen according to the empirical literature on Beijing and real modal splits in Beijing (see Table 3). The travel cost for walking is set as 0. The variable travel cost of a private car $c^{1,car}$ is 0.3 CNY per km, and gasoline price $c^{2,car}$ is 6.2 CNY per liter. The variable cost of public transport $c^{1,public}$ is 0.2 CNY per km, while its fixed cost $c^{3,public}$=1.5 CNY.

When distance from downtown increases, the road-land proportion declines gradually with an average predetermined value according to real traffic conditions in Beijing. Speed limits vary among different zones; for example, the free flow travel speed in zone 1 (9) is set at 44 km/h. Owing to the increasing density of traffic lights closer to downtown, free travel speeds are set up as decreasing evenly along the zones inward. The values of BPR function parameters $b$ and $c$ refer to data from the US Bureau of Public Roads. The average $CO_2$ emission of public transport is specified as ASCE = 11.9 g/pkm, and the efficiency coefficient in gasoline consumption and $CO_2$ emission is e = 1.26, following the average $CO_2$ emission of public transport and the gasoline consumption in benchmark equilibrium with the results of related studies [32].

Based on the established SCGE model and the parameters in Table 1, benchmark equilibrium can be obtained using GAMS; some of the results are listed in Table 2. Rent declines steeply with distance from the city center, and the rent downtown is much higher than in suburban areas. This is mainly due to the notion that land is immobile, and land supply increases with distance from downtown, while land near the city center is in much greater demand for residences, production, and road planning. Traffic flow reaches a summit downtown, giving rise to an especially obvious supply-demand conflict, explaining the high rent downtown compared to other zones. By contrast, labor supply and output are elastic in different zones. With increasing rent, firms are inclined to substitute labor for land, resulting in augmented labor demands. Labor is in greater demand downtown, but the supply increases relatively more, causing wages to reduce gradually in a smooth manner. Influenced by both rent and salaries, product prices are higher in zones near downtown; downtown prices are 1.7 times higher than in suburban areas. Moreover, the total output downtown is actually limited by the total land area, which is the lowest amongst all zones and accounts for 38% of production in the most distant suburban areas.

Furthermore, residence land ratio and average housing area are higher in zones further away from downtown. The housing area per capita in distant suburban areas is more than six times that of downtown. As for residence population, downtown has the lowest residence population,

Table 2: Partial results of benchmark equilibrium.

| | Zone 1 (9) | Zone 2 (8) | Zone 3 (7) | Zone 4 (6) | Zone 5 |
|---|---|---|---|---|---|
| Rent $r_i$ (¥/m$^2$/a) | 200 | 250 | 320 | 400 | 1200 |
| Product price $p_i$ (¥/unit) | 96.624 | 101.843 | 108.127 | 113.720 | 162.286 |
| Output $X_i$ (million/a) | 3.1720 | 3.1955 | 2.8373 | 2.4420 | 1.2089 |
| Housing area per capita $q_i$ (m$^2$) | 77.834 | 61.964 | 47.309 | 36.869 | 12.127 |
| Housing population | 14242 | 14644 | 11686 | 8507 | 1842 |
| Employment population | 13394 | 13152 | 11200 | 8786 | 6939 |
| Job–housing balance ratio | 0.940 | 0.898 | 0.958 | 1.033 | 3.767 |
| Housing population density (p/km$^2$) | 2550 | 3496 | 4185 | 6093 | 5276 |
| Gasoline consumption of private cars (l/km) | 0.095 | 0.098 | 0.107 | 0.138 | 0.169 |
| $CO_2$ emissions of private car (g/km) | 277.24 | 288.08 | 311.98 | 404.78 | 495.63 |

Table 3: Comparison of benchmark equilibrium results with empirical evidence.

| Parameter | SCGE value | Empirical value | Empirical source and explanation |
|---|---|---|---|
| Average hourly wage (¥/h) | 24.48 | 24.23 | *Beijing Statistical Yearbook 2016*, annual disposable income/2000 hrs |
| Average job–housing distance (km) | 6.77 | 6.4 | Reference [28] |
| Average commuting time (h) | 0.545 | 0.583 | Reference [28] |
| Public transport split rate | 50.1% | 50% | *Beijing Traffic Development Annual Report 2016* |
| Cross-price elasticity of demand for public transport with respect to gasoline price | 0.2 | 0.1–0.8 | Reference [29] |
| Own-price elasticity of demand for private car with respect to gasoline price | -0.5 | -0.1– -0.5 | Reference [30] |
| Own-price elasticity of demand for public transport with respect to fare | -0.035 | -0.0171 (bus)<br>-0.1538 (subway) | Reference [31] |
| Ratio of commuting travel to total travel | 50.50% | 51.96% | *Beijing Traffic Development Annual Report 2016*, including school commuting |
| Ratio of transport expense to total disposable income | 6.5% | 6.8% | *Beijing Traffic Development Annual Report 2016*, commuting expense/ disposable income |

and the urban zones have more while the suburban zones have the most. There are no distinct differences in residence population numbers among suburban zones. As for the working population, downtown has the least—almost half that of suburban areas.

In terms of job-housing balance, downtown is a job-rich area, while the suburban zones are housing-rich areas; urban zones are relatively balanced. Therefore, housing density tends to decrease from downtown outward to the suburban areas; thus, suburban housing density is far less than downtown housing density. It has been shown that the gasoline consumption and $CO_2$ emission of private cars in 1 km of travel diminish with diminishing traffic congestion. Although the differences between zones are relatively small, gasoline consumption and $CO_2$ emission escalate downtown and near downtown due to the serious traffic congestion.

To further investigate the model's authenticity—especially the accuracy of the traffic condition description—we compare some of the key results in the benchmark equilibrium with the corresponding empirical values (Table 3). The simulation results are shown to be approximate to the empirical values, including average salary per hour, average job-housing distance, average commute time, public transport split rate, ratio of commuting travel to total travel, and ratio of transport expense to total disposable income, among others. The transport-related elasticity coefficients comply with the empirical value ranges given in the references. Thus, the constructed SCGE model is reliable and applicable to the simulation analysis of public transport subsidies in Beijing.

## 4. Simulation Results and Discussion

*4.1. Scenario Design.* Here, we present four different simulation policies.

*Scenario 1* (change the public transport fare subsidy rate). From 2007 to 2014, the local government of Beijing had implemented a policy where passengers with a bus IC card could travel on buses at a 60% discount. With the new fare policy in 2015, the subsidy rate was decreased to 50%. Thus, the public transport fare subsidy rate in the benchmark equilibrium is $s^{public} = 0.5$, set based on the current policy. In Scenario 1, the fare subsidy rate will be changed to varied levels, and the effects caused by the changes are discussed.

*Scenario 2* (substitute cash grant for fare subsidy). Here, the public transport subsidy rate $s^{public}$ decreases to 0, and a fund is granted to increase cash subsidy $S$. In China, most of the employed population is not covered by cash transport grants, except for minority groups such as civil servants, so the one-time cash grant is determined as $S$=0 in the benchmark equilibrium. Scenario 2 simulates the implementation of a cash grant policy and compares the outputs with other scenarios under the same total subsidy budget level.

*Scenario 3.* The subsidy fund is invested in the road capacity expansion of urban areas (zones 3–7). This means $s^{public}$ decreases to 0, and the fund is allocated to increase the proportion of road land. The simulation under this condition considers whether subsidizing passengers or improving road infrastructure is more efficient using the same amount of money. The cost of road expansion is calculated by the rental opportunity cost of the additional urban land allocated to roads (in Beijing, public-private partnerships between government agencies and private-sector companies are used to finance, build, and operate many projects, including public transport networks. For simplicity, it is assumed that the private-sector company affords the labor, machine, and raw materials costs of road construction. For the local government, the main cost is land input. Because this study aimed to investigate government subsidy, it is assumed that road expansion costs for the government consist only of the rental opportunity cost of the additional urban land allocated for roads).

*Scenario 4.* The subsidy fund is invested in public transport speedup. When $s^{public}$ decreases to 0, the fund is spent on improving average public transport travel speed. Public transport speedup may result from updating bus vehicles, rescheduling routes, and adding bus lanes. After the speedup, the average travel time by public transport will be reduced. Thus, the subsidy cost of public transport speedup is calculated by the time opportunity cost of reduced travel time for public transport travelers (speedup policy is considered to subsidize time cost, which equals the benefit the policy brings to travelers).

All simulations mentioned above are based on the benchmark equilibrium level where the fare subsidy rate is 0.5 and the fluctuating step is 0.1 for the rate. By increasing and decreasing the corresponding subsidy amount, the effects on social welfare, population, and $CO_2$ emissions are examined.

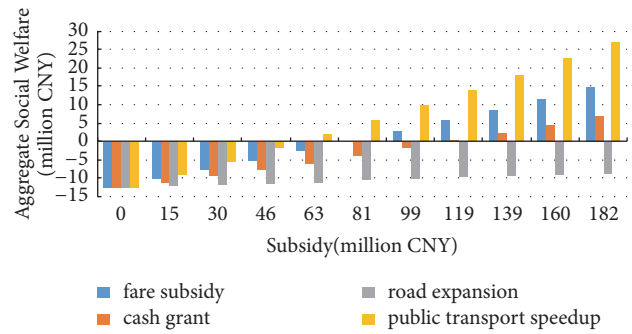


Figure 2: Social welfare effects of four transport subsidy policies.

*4.2. Social Welfare Effects.* When the public transport fare is completely subsidized, the subsidy fund amount is 182.36 million CNY, where the subsidy level ranges from 0.00 to 182.36 million CNY under Scenarios 1–4. Figure 2 shows the social welfare effects tendency under four policies when the fare subsidy rate changes from 0 to 1, while the total subsidy amount increases from 0.00 to 182.36 million CNY.

The horizontal axis represents the total subsidy amount with different fare subsidy rates from 0 to 1. For example, the total subsidization amount of ¥99.12 million corresponds to public transport fare subsidy rate $s^{public} = 0.6$, cash grant S = ¥ 991, 10.95% improvement in road land use rate, or public transport speedup to 21.4 km/h. The vertical axis depicts social welfare effects under four policies, which are calculated as the expected value of the maximized utilities, as in (8).

As shown in Figure 2, if the fare subsidy rate decreases from the current value of 0.5 to 0, overall social welfare will decline by 12.6293 million CNY, implying that average social welfare decreases by 2.526 million when the subsidy rate drops by 0.1. However, if the government gradually raises the fare subsidy rate to 1, overall social welfare will increase by 14.4774 million. Specifically, social welfare increases on average by 2.896 million with 0.1 increments in the subsidy rate. If the current fare subsidy is canceled and the same subsidy fund amount is distributed in the form of cash, overall social welfare will be lower than in the benchmark equilibrium by 3.9751 million. Only when total subsidization increases to 118.56 million, corresponding to a fare subsidy rate of 0.7, will the social welfare in the benchmark equilibrium be achieved.

Otherwise, as the total amount of subsidization increases, the aggregate social welfare under all four scenarios shows an uptrend. However, the ascending rate varies for each policy. Among them, Scenario 4 has the fastest increase rate, followed by Scenarios 1 and 2, while Scenario 3 increases the slowest. If public transport speedup policy is implemented, the benchmark equilibrium social welfare level can be obtained by investing less than 70 million, equivalent to a fare subsidy rate of 0.35. Meanwhile, when the subsidy fund is used to expand road capacity, even if all 182.36 million is invested, overall social welfare will remain substantially below the benchmark equilibrium level. This indicates that subsidizing public transport speedup has the most significant influence on social welfare, followed by fare subsidy and

Table 4: Spatial effects of four public transport subsidy policies.

| Subsidy(millions) | Scenario | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Scenario 1 | | | Scenario 2 | | | Scenario 3 | | | Scenario 4 | | |
| | 14.55 | 80.55 | 182.36 | 14.55 | 80.55 | 182.36 | 14.55 | 80.55 | 182.36 | 14.55 | 80.55 | 182.36 |
| Urban residents | +402 | 0 | -554 | +499 | +519 | +547 | +548 | +756 | +995 | +335 | -509 | -2115 |
| Urban residents ratio (%) | +0.95 | 0.0 | -0.07 | +1.18 | +1.23 | +1.29 | +1.30 | +1.79 | +2.36 | +0.79 | -1.21 | -5.01 |
| Urban employed population | -34 | 0 | +61 | -9 | +137 | +359 | +1 | +170 | +361 | -82 | -361 | -1054 |
| Urban employed population ratio (%) | -1.31 | 0.0 | +0.13 | -0.02 | +0.29 | +0.77 | 0.00 | +0.36 | +0.77 | -0.17 | +0.77 | -2.25 |
| Interzone commuting ratio (%) | -27.13 | 0.0 | +41.85 | -32.67 | -31.32 | -29.20 | -32.70 | -31.52 | -30.10 | -23.11 | +33.73 | +159.83 |
| Interzone shopping ratio (%) | -9.22 | 0.0 | +12.63 | -11.40 | -11.49 | -11.62 | -11.40 | -11.46 | -11.49 | -7.78 | +10.54 | +45.05 |
| Innerzone commuting ratio (%) | +2.51 | 0.0 | -3.61 | +2.99 | +2.57 | +1.93 | +2.94 | +2.34 | +1.64 | +2.14 | -2.04 | -8.10 |
| Innerzone shopping ratio (%) | +1.64 | 0.0 | -2.30 | +2.20 | +2.05 | +2.09 | +1.90 | +1.44 | +0.90 | +1.31 | -1.77 | -6.10 |

cash grant, while road capacity expansion has relatively little effect. This is because public transport speedup significantly shortens travel time for consumers, leading directly to more working time and output, and indirectly to more product consumption. For instance, when public transport speed increases to 29.67 km/h, total output grows by 2.04% compared to the benchmark speed of 15 km/h. Yet, road expansion policy is hampered by the high land rent in urban areas. Although it can contribute to curtailing travel time and the cost of private cars, the population benefit from road expansion is less than in other scenarios, and the influence is less critical; thus, road expansion policy has no apparent role in boosting overall social welfare.

*4.3. Job-Housing Spatial Effects.* Various public transport subsidy policies have effects on citizen job-housing location, which can be measured by changes in the population distribution of residences and employment in different zones, as well as changes in short- and long-distance travel ratios. Table 4 shows variations in residence and employment distributions in urban areas compared to the benchmark equilibrium under the four subsidy policies when the total subsidizations are 14.55, 80.55, and 182.36 million, as well as the changes in inter- and innerzone commuting and shopping travel.

As shown in Table 4, under Scenario 1, as the subsidy fund increases, residents in urban areas are reduced, and resident distribution is mildly prone to suburbanization, with the residential ratio decreasing by 0.07% if the fare rate changes from 0.5 to 1. However, the employed population does not display an outward trend, and even a slight population aggregation to urban areas occurs. The main reason for this is that fare subsidy policy lowers travel costs and therefore encourages consumers to choose areas with cheaper living costs. However, the choices for working places mainly depend on average hourly wages, so the employed population tends to assemble in urban areas. This produces a significant increase in interzone commuting and shopping and a decrease in innerzone commuting and shopping. The results indicate that fare subsidy policy is not helpful for employed population suburbanization; it can only assist in encouraging residents to move outward to suburban areas and to travel longer distances.

Under Scenarios 2 and 3, public transport subsidies have similar effects on population distribution. When subsidization increases, both residential and employed populations converge on urban areas and downtown, and the convergence of the residential population is greater than that of the employed population. For example, when the total subsidization is 182.36 million, urban residential populations under two policies increase by 547 and 995, respectively, compared to the benchmark equilibrium, while the employed populations increase by 359 and 361, respectively. Interzone commuting and shopping travel reduce remarkably, while innerzone commuting and shopping travel gain modest growth. This is because, in general, cash grants can enlarge consumers' disposable incomes. Meanwhile, road expansion can reduce both the travel time of urban private cars and travel costs. In short, subsidizing public transport, either through cash distribution or road infrastructure construction, intensifies urban agglomeration.

Contrary to Scenarios 2 and 3, residential and employed populations show suburbanization to some extent under Scenario 4, and the suburbanization degree for the employed population is lower than that of the residential population. For example, when the total subsidization is 182.36 million, residential and employed population ratios in urban areas decrease by 5.01% and 2.25%, respectively, compared to the benchmark equilibrium level. Meanwhile, interzone commuting and shopping travel ratios increase by 159.83% and 45.05%, respectively, while innerzone commuting and shopping ratios decrease somewhat. Clearly, public transport speedup can stimulate long-distance commuting and shopping travel by decreasing travel time, thus strengthening urban sprawl. Therefore, public transport speedup can help relieve the urban agglomeration of residential and employed populations.

*4.4. Environmental Effects.* The effects of subsidy policies on the environment are embodied in changing consumers' travel modes and reducing pollution. Therefore, environmental effects are measured by changes in the public transport split rate and travel-related $CO_2$ emissions (for more details on the environmental consequences of $CO_2$ emissions, see cost analyses of carbon emissions, such as Tong et al. (2017)).

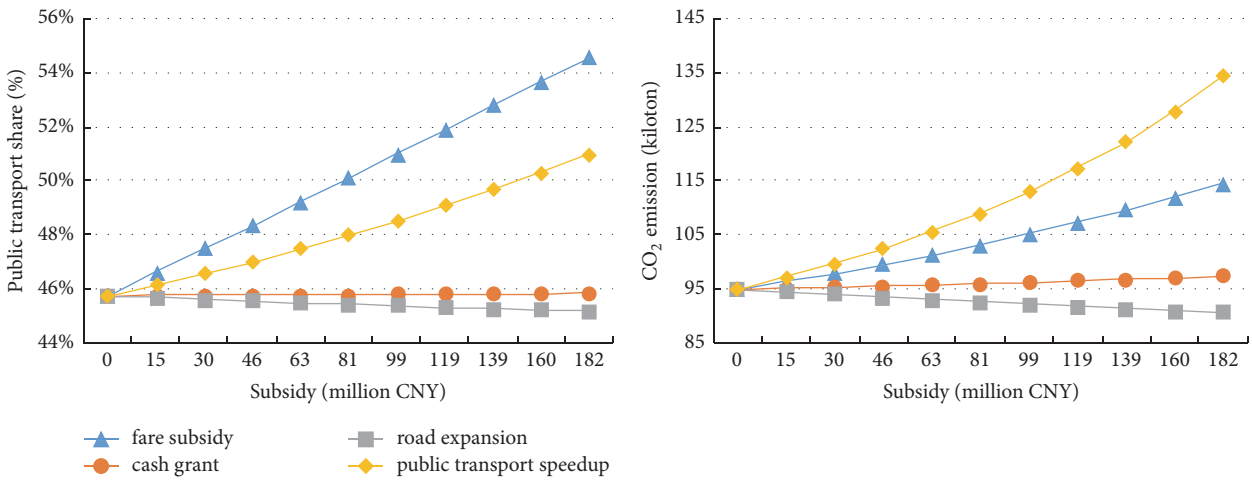


Figure 3: Environmental effects of four transport subsidy scenarios.

Figure 3 compares public transport split rates under different subsidy scenarios. Scenarios 1, 2, and 4 are shown to improve the public transport split rate to some degree. In general, however, the improvement effects are not remarkable. Among the scenarios, the effect of fare subsidy is relatively outstanding. When the fare subsidy rate increases from 0 to 1, the public transport split rate rises to 54.54% from 45.77%. If the same amount of subsidization is invested in public transport speedup, the effect is less significant, and the split rate improves to 50.99% with a total subsidization of 182.36 million. Otherwise, if the subsidy fund is granted by cash, which exerts the smallest influence, the split rate stays at almost the original level of 45.8%. However, with subsidization used for road expansion, the split rate decreases inconsiderably to 45.19%. This is because expanding road capacity can lower congestion and thus reduce both travel time and travel cost for urban private cars. When congestion decreases, traveling by private car becomes more attractive.

Figure 3 also shows the $CO_2$ emissions generated by transport with varying subsidization levels under different policies. In reality, governments usually consider transport subsidy as a tool for reducing $CO_2$ emissions. However, the simulation results show that whether $CO_2$ emissions are reduced depends on the type of subsidy policy. As shown in Figure 3, Scenarios 1, 2, and 4 increase travel-related $CO_2$ emissions, while Scenario 3 reduces emissions. This is mainly because road expansion has two effects on $CO_2$ emissions. First, the $CO_2$ emissions of 1 km of travel by private car are reduced because of the faster speed. Second, as mentioned above, both residential and employed populations are converging on urban areas and downtown. Interzone commuting and shopping travel are remarkably reduced, while innerzone commuting and shopping travel gain modest growth. This means less total travel distance. Both effects lower $CO_2$ emissions. Thus, even though the public transport split rate declines mildly, an apparent decline in travel-related $CO_2$ emissions occurs. The other three policies trigger more consumer traveling by lowering shopping costs, increasing income, or amplifying production. As for public transport speedup, it can reduce travel time to produce more aggregate output, which will trigger more consumer trips. It can also stimulate long-distance commuting and shopping travel by decreasing travel time. The other two policies, fare subsidy and cash grant, trigger more consumer traveling by lowering shopping cost and increasing income. Thus, traffic-related $CO_2$ emissions still increase, even though the public transport split rate increases or stays the same. This tells us that traffic-related $CO_2$ emissions are determined by travel mode preferences and travel frequency. $CO_2$ emissions are definitely augmented when the negative effects of more frequent travel outweigh the positive effects of higher public transport shares.

## 5. Conclusion

With job-housing spatial choice predetermined as the endogenous variable, this study constructed a SCGE model containing firms, consumers, and transport modules in one framework to investigate the effects of public transport subsidies. Using a benchmark equilibrium calibrated for Beijing, the model simulated social welfare, population distribution, and travel-related $CO_2$ emission effects under different subsidization levels with four forms of subsidy policies: fare subsidy, cash grant, road expansion, and public transport speedup. The conclusions from the simulation studies are summarized below.

First, public transport subsidies can enhance overall social welfare, regardless of what form the policy takes. Moreover, public transport speedup has the strongest effect on social welfare, followed by fare subsidy, cash grant, and road expansion, respectively.

Second, different forms of public transport subsidies can exert varied influences on city job-housing population distribution. Cash grant policy and road expansion construction encourage urban agglomeration, and residential populations aggregate more densely than employed populations. Fare subsidy policy affects employed population distribution only slightly but stimulates residential population diffusion

to suburban areas. In addition, public transport speedup suburbanizes both residential and employed populations, and residential populations show a stronger suburbanization, which can alter population convergence on the downtown area.

Third, most public transport subsidy policies give rise to modestly higher public transport split rates. Comparatively, fare subsidies have the most apparent effect, followed by public transport speedup, while cash grants have no influence on public transport share. Road expansion, however, acts in the opposite way, slightly reducing public transport share.

Fourth, except for road capacity expansion, public transport subsidy policies do not reduce travel-related $CO_2$ emissions. In fact, fare subsidy, cash grant, and public transport speedup policies all stimulate higher travel frequency among consumers and therefore aggravate total travel-related $CO_2$ emissions. $CO_2$ emissions can only be reduced by investing subsidies in road expansion construction.

In conclusion, the social welfare, spatial, and environmental effects of the four subsidy policies are quite different. Therefore, when governments decide on the level and form of public transport subsidization, the strategic goal of the subsidy policy should be ascertained by combining local conditions. By matching the goal with the subsidy form and considering the fiscal budget, an appropriate public transport subsidy plan can be established and recommended. For example, if the subsidy policy aims to improve social welfare, then a public transport speedup policy (e.g., setting up more bus lanes or renewing vehicles) is recommended. If the subsidy policy aims to control $CO_2$ emissions, road expansion construction should be prioritized. Finally, if the subsidy policy aims to encourage people to use public transport, a fare subsidy policy would be the most appropriate approach.

## Data Availability

The data used for model calibration were mainly derived from the Beijing Statistical Yearbook 2016 and the Beijing Traffic Development Annual Report 2016, which can be found at http://www.bjstats.gov.cn/tjsj/ndtjzl/2018ndtjzl/index.html and http://www.bjtrc.org.cn/JGJS.aspx?id=5.2&Menu=GZCG, respectively. The simulation results exported from our GAMS program are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest.

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