Article

Urban Studies

Urban Studies
1–19
© Urban Studies Journal Limited 2015
Reprints and permissions:
sagepub.co.uk/journalsPermissions.nav
DOI: 10.1177/0042098015594072
usj.sagepub.com
SAGE

Losers and Pareto optimality in optimizing commuting patterns

Jiangping Zhou
The University of Queensland, Australia

Ying Long
Beijing Institute of City Planning, China

Abstract

When optimising the overall commuting pattern for a city or a region, there are often winners and losers among commuters at the subdivision level. Losers are those who are burdened with longer commutes than before the optimisation. Knowing who or where losers are is of interest to both researchers and policy-makers. The information would help them efficiently locate losers and compensate them. Few, however, pay attention to such losers. By revisiting "excess commuting" in the economic framework, we show that optimising the commuting pattern is comparable to restoring Pareto optimality in commuting. Using Beijing as a case study, we identify and geo-visualise the losers when the city's bus commuting pattern is optimised. We examine the severity of the loss among the losers, the spatial pattern of the losers and their influencing factors. We find that most losers are located around the epicenter. The severity of the loss is independent of jobs/housing ratio but is associated with the commute distance before the optimisation. Workers whose commute distance is less than the global average are more likely to become losers. Places where losers reside have significantly lower employment density in a few industries than where non-losers reside. A low jobs/housing ratio in individual subareas does not necessarily increase the average trip length of commuters therein. A low jobs/housing ratio of one or several subareas, however, could influence the average trip length of all the commuters in the area. Locating diverse jobs and housing opportunities around or along transit corridors could compensate the losers and reduce the overall commuting cost.

Keywords

excess commuting, geo-visualisation, losers, policy implications, system optimal

Received November 2014; accepted May 2015

Introduction

Commuting accounts for a significant share of trips that workers make daily. If most workers drive alone and have a long commute, they contribute to or even constitute

Corresponding author:
Jiangping Zhou, School of Geography, Planning and Environmental Management, The University of Queensland, Brisbane, Queensland, 4072, Australia.
Email: zhoujp@gmail.com

some of the most challenging problems of our times: car dependency, traffic congestion and resultant air and noise pollutions. The jobs/housing balance thus has been advanced as a strategy to optimise the transportation-land use system in general and the jobs/housing balance in particular in cities/regions (Boarnet et al., 2011; Niedzielski et al., 2013). The jobs/housing balance refers to the level of heterogeneity among workers' residences and employment locations in a predefined area, where an appropriate mix of jobs and housing opportunities is regarded as beneficial in terms of alleviating the aforementioned problems (Cervero, 1989).

In light of the above, many have attempted to quantify the jobs/housing imbalance and associated "excess commuting". To simplify, they assume that all workplaces and residences are homogeneous and workers can be enticed to any workplace or residence in a given city. Based on these assumptions, excess commuting can then be defined as "the nonoptimal or surplus work travel occurring in cities because people do not minimise their journeys to work" (Horner, 2002: 543). Non-excessive commuting is where the actual commute (T_{act}) is equivalent to the theoretical minimum commute (T_{min}) where individuals travel to the closest possible workplace on average in terms of some measure of zonal separation (e.g. time, distance). T_{min} measures the relative jobs/housing balance for a given distribution of jobs and housing locations; that is, it is a fixed urban form (Horner, 2002). We now know T_{min}, T_{act} and excess commuting for a notable number of cities or regions and what may affect them (e.g. see Ma and Banister, 2006 for a review of related literature). In other words, there has been a mini academic industry of excess-commuting studies. Metrics in this industry, especially those developed post-2002 do not vary with scale (Niedzielski et al., 2013). Thus, they may universally apply regardless of scale, providing us with some reliable indicators for studies of phenomena such as the jobs/housing balance, excess commuting and commuting efficiency. Few, however, pay attention to "losers" at the subdivision level when T_{min} is achieved, i.e. the global commuting costs are minimised at the expenses of some workers. Here, we define losers as workers in the subdivisions who, when T_{min} is achieved at the global level, are burdened with longer commutes than the status quo.

For a given study area, if our starting points are that T_{act} does not equal to T_{min} and that commuting costs are the only utility we care about, losers always exist because the global commuting costs can only be minimised when some commuters swap their residences and/or workplaces. Excess commuting, i.e. the differences between T_{act} and T_{min}, is somewhat comparable to the "deadweight loss" in economics. The latter occurs when equilibrium for a good or service is not achievable. Excess commuting is zero when no worker can unilaterally change their residential/work locations to improve their commuting times/costs. Zero excess commuting is comparable to Pareto optimality, which describes a state of allocation of resources in which it is impossible to make any one individual better off without making at least one individual worse off. Non-zero excess commuting arises because some workers unilaterally change their residential/work locations to improve their perceived commuting times/costs. Unilateral behaviours of workers lead to non-Pareto improvement for all the workers in question. In light of the above, we can argue that existing commuting patterns in most cities are not Pareto optimal. Optimising those patterns means "restoring" Pareto optimality.

Assuming that our primary goal now is Pareto optimality for overall commuting patterns in cities, then knowing who or where the losers are would be of great

interest to both researchers and policy-makers. The knowledge would enable them to design appropriate intervention mechanisms such as financial subsidies to losers or accurate travel, housing and job information for all workers so as to promote Pareto optimality. Using bus commuter information derived from smartcard data in Beijing, we identify and geo-visualise the losers when bus commuting patterns are optimised. We also examine the severity of the loss among the losers, the spatial pattern of the losers and their probable influencing factors. Based on our empirical findings, we discuss transferable planning and policy implications.

The remainder of this article is organised as follows: Section 2 reviews related literature so as to find where this study can be placed and how it can advance related research therein. Section 3 defines the key concepts of this article: losers and winners in the commuting pattern optimisation. Section 4 presents an empirical study, where bus smartcard data are used to generate the input data. Section 5 concludes and discusses future research directions.

Literature review

Excess commuting at the city/regional levels

Hamilton (1982) is a pioneer in studying whether T_{act} deviates from T_{min} and in quantifying the differences between the two values, that is, "wasteful" or excess commuting. In his study, he uses the monocentric models to predict T_{min} in urban areas. He finds that T_{act} is about eight times greater than that predicted by the model wherein workers are assumed to minimise their overall commuting costs. He also calculates the volume of commuting which would result if people chose their houses and jobs at random, making no effort to economise on commuting. This over predicts actual commuting by about 25 percent. White (1988) abandons the monocentric models and utilises an alternative assignment model ("Transportation Problem of Linear Programing" (TPLP)) to calculate excess commuting of a sample of cities, some of which overlap those of Hamilton (1982). The other type of T_{min} can be found by solving a TPLP (White, 1988). When T_{min} and T_{act} are quantified, Excess Commuting (*EC*) is formulated as the following:

$$EC = \left(\frac{T_{act} - T_{min}}{T_{act}}\right) * 100 \qquad (1)$$

Based on TPLP, White (1988) finds that only around 11 percent of actual commuting in urban areas that Hamilton (1982) studies is excessive. Later, TPLP is employed to quantify excess commuting in a wide array of cities in North America and Europe (Buliung and Kanaroglou, 2002; Charron, 2007; Frost et al.1998; Giuliano and Small, 1993; Hamilton, 1989; Horner 2002, 2010; Merriman et al., 1995; Murphy, 2009; Murphy and Killen, 2011; Scott et al., 1997). When applying TPLP to optimising commuting, key assumptions authors made are: AQ1 AQ2

1. All workers are homogeneous in terms of their skills and preference;
2. All jobs and residences are homogeneous and are open to any workers;
3. Workers can be enticed to any job and/or residence;
4. Commuting costs are the only utility that is considered.

The above assumptions are made in this article too. We could have considered more factors such as people's willingness to pay, relocation and job availability. Our work has stuck to a standard TPLP so that we could more efficiently identify and profile losers in a simpler model.

T_m and *EC* can be linked to other concepts such as the jobs/housing balance, the qualitative and quantitative balances of jobs and homes and commuting efficiency. For instance, T_{min} can indicate the relative balance of jobs with respect to housing in a region (Small and Song, 1992). There are two types of balances of jobs and homes: qualitative and quantitative (Ma and Banister, 2006). The quantitative balance is achieved when T_{act} equals to T_{min} while the qualitative imbalance emerges when there is the mismatch between workers' characteristics such as willingness to pay, desired housing features and residential preference and the actual supply of housing (Giuliano, 1991). Thus, wherever there is the qualitative imbalance, T_{act} is greater than T_{min}.

How should we define the appropriate unit when we study the jobs/housing balance? For some researchers, the jobs/housing balance concerns "the spatial relation between the number of jobs and housing units within a given geographical area" and this is normally represented as a ratio at the level of a zonal unit such as a census tract or Traffic Analysis Zone (TAZ) or at the aggregate regional level (Peng, 1997: 1216). For others, the jobs/housing balance should consider jobs or employment opportunities not only within a predefined area but also around it. Levinson (1998) applies an accessibility measure for the jobs/housing balance to account for jobs or housing units in and around a zone according to some spatial distance decay functions. He argues that this measure is more powerful than zone-based jobs/housing ratios in terms of explaining the variations in commuting. His case studies show that accessibility to jobs and housing has a negative relationship with distance, and that transit commuters appear to have higher accessibility than automobile users.

Commuting efficiency is a concept by Horner (2002). A high commuting efficiency means a low excess commuting value and a good jobs/housing balance. Commuting efficiency should be measured by commuting capacity used (C_u) as well as Excess Commuting (*EC*, see Eq. 1). C_u provides a gauge of how much of the available commuting range has been consumed in a city or a region. When comparing commuting efficiency of cities, both excess commuting and C_u should be considered. There could be cases in which the differences of the excess commuting values of two cities could be much greater than the differences of their respective C_u values. In other words, one city's commuting patterns can be more efficient than the other city when *EC* is used as the only indicator but it can have a larger C_u value. To get C_u, Horner (2002) introduces a new indicator: the theoretical maximum commute (T_{max}). T_{max} can also be found with TPLP. C_u is calculated as:

$$C_u = \left(\frac{T_{act} - T_{min}}{T_{max} - T_{min}}\right) * 100 \qquad (2)$$

Excess commuting at the sub-regional or subarea levels

At the sub-regional level, a better jobs/housing balance is found to be significantly but weakly associated with a smaller theoretical minimum commute in Los Angeles. Therefore there are factors other than commuting costs that influence the location decision of workers and their commuting therein (Giuliano and Small, 1993). At the zonal level, cities having a better jobs/housing balance are associated with a shorter actual commute (Horner, 2002). In the case study of Atlanta, when both changes in journey-to-work flows and locations of workers and jobs are allowed in TPLP, it is found that (a) a better jobs/housing balance reduces the theoretical minimum commute; (b) relocating workers (e.g. promoting higher residential density in selected areas) tends to be more feasible and effective than relocating

jobs in terms of reducing the averaging commuting; (c) even relocating a small percentage of workers could generate substantial savings in the average commuting (Horner and Murray, 2003).

In the studies of four Polish cities, Niedzielski (2006) shows that excess commuting varies across the cities and estimates of commuting efficiency are influenced by the jobs/housing balance and are sensitive to locations of zones within the study area. He introduces six measures similar to Eqs. (4) and (5) outlined below.

For any study areas, the jobs/housing balance can be evaluated using both regional and localised measures of commuting and land use (Horner, 2007). The regional measures are theoretical minimum/maximum commutes and actual commute, which have been frequently measured in existing studies (e.g. Horner 2002; Horner and Mefford, 2007; Murphy, 2009). The localised measures are only occasionally used (Giuliano and Small, 1993; Horner, 2007; Niedzielski, 2006). Among them, three localised indices of particular interest to this study are: worker-jobs ratio (B_i), the origin-specific average outbound commute of workers living a zone (ω_i) and the destination-specific average commute of workers inbound to a zone (μ_j). The formulations for B_i, ω_i and μ_j are as follows:

$$B_i = O_i/D_i \tag{3}$$

where O_i is the total workers in zone i and D_i is the total employment in zone i.

$$\omega_i = \frac{\sum_j C_{ij}X^*_{ij}}{\sum_j X^*_{ij}} \tag{4}$$

$$\mu_j = \frac{\sum_i C_{ij}X^*_{ij}}{\sum_i X^*_{ij}} \tag{5}$$

where

C_{ij} = travel cost from zone i to zone j, which can be measured in length, time or money;

X_{ij} = number of trips from zone i to zone j.

The superscript "*" indicates multiple types of commute matrices, for instance, the matrices associated with T_{act}, T_{min} and T_{max} (Horner, 2007).

Key concepts

To best profile and quantify losers and winners, let's introduce two new indicators: the origin-specific average outbound commute of workers living a zone i (ω_i') and the destination-specific average commute of workers inbound to zone j (μ_j') when the commuting pattern is optimised at the city/regional levels:

$$\omega_i' = \frac{\sum_j C_{ij}X^{min}_{ij}}{\sum_j X^{min}_{ij}} \tag{6}$$

$$\mu_j' = \frac{\sum_i C_{ij}X^{min}_{ij}}{\sum_i X^{min}_{ij}} \tag{7}$$

Eqs. (6) and (7) use the same denotations as Eqs. (3) to (5), except that X^{min}_{ij} is the number of trips from zone *i* to zone *j* when the global commuting pattern is optimised, that is, when T_{min} is achieved. For any given zone, if μ_j' or ω_i' is greater than ω_i or μ_j, respectively, we call workers or commuters therein losers. Figure 1 illustrates how losers arise when we optimise the commuting pattern of a study area.

In Figure 1, there is a hypothetical city with a total of nine homogeneous workers who can be enticed to any of 10 zones, among which five are origins (circles in the figure) where workers reside and five are destinations (rectangles in the figure) where workers work. Before the overall commuting pattern is optimised, the worker residing in Zone B commutes outbound to Zone 1 and

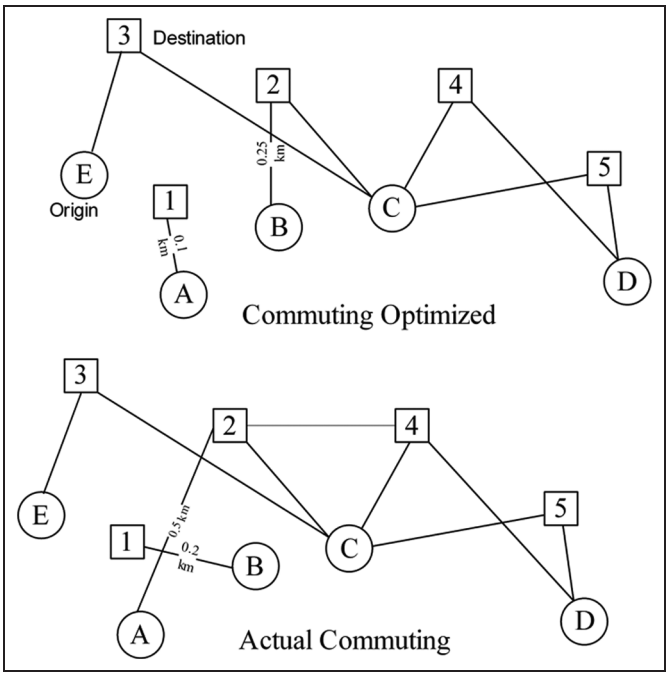

Figure 1. Illustration of how losers arise.

enjoys the shortest commute (ω_b = 0.2 km) in the city. After the overall commuting pattern is optimised, the worker residing in Zone B would have to commute to Zone 2 and his/her commute (ω_b' = 0.25 km) is now longer than before. But because of her/his "sacrifice", the worker from Zone A now can work in Zone 1, which now sees a reduction in its worker' inbound commute (μ_1 = 0.1 km). For all the workers, after the above relocations, they as a whole reach Pareto optimality. In this state, excess commuting is zero and no worker can unilaterally change their residential/work locations to shorten their commuting distance without increasing the overall commuting distance.

In the context of urban planning or transportation policy, there could be several explanations for why workers in a city cannot achieve Pareto optimality or lose it. Let's illustrate still using the above hypothetical city as an example. The first explanation is exclusionary land use planning or zoning where mixed land use is discouraged. When Zone 1 only allows high-tech industries, for instance, the low-skilled worker residing in Zone A would have to commute to Zone 2 where all industries are allowed.

The second explanation is information asymmetry. When employers and workers do not have the same amount of information regarding the labor market, workers would search for jobs in areas where they have the most relevant information. Thus, if we assume that the worker residing in Zone A knows more about employment opportunities in Zone 2 than in any other zones, she or he would be most likely to end up working in Zone 2.

The third explanation is inappropriate subsidies. To attract businesses, many cities provide tax rebates or rent subsidies. This could distort the labour and land markets,

which can lead to non Pareto optimality in commuting. Assume that initially all the five zones offer nothing to attract businesses and Pareto optimality is achieved. For some reason Zone 2 starts heavily subsidising businesses therein. As a result, the employment that matches the skills of the worker residing in Zone A is relocated to Zone 2. Then this worker would have to work in Zone 2 rather than in Zone 1. At this point, the state of commuting in the city would move away from Pareto optimality.

The fourth explanation is pricing ceilings or floors, particularly minimum wages. For instance, when Zone 1's minimum wages are higher than all other zones, employers therein would all move to Zone 2 where minimum wages are not required, forcing the worker in Zone A who is despairing for a job to commute to Zone 2 to work.

The following section describes how we quantify the number of losers when bus commuting patterns in a real city are optimised, and where they are. We also examine the spatial distribution of the losers, the severity of the loss and their influencing factors in the specific context.

Empirical studies

The site and data

Beijing is our site for the empirical studies. As the capital of China, Beijing now has over 22 million residents and is one of the most populous cities in the world. The land area of the Beijing metropolitan area is 16, 410 km^2. Table 1 shows the modal share breakdown of trips for 2008 and 2010 in Beijing. It can be seen that the car is the dominant mode of travel, with its use on the increase. On the other hand, the bus is the dominant form of public transport and its share has remained more or less constant over the period with a large increase seen in the use of the subway. It is notable also, that contrary to many world cities where the share of biking and walking is increasing (see Murphy and Usher, 2013), the trend in Beijing is for a decline in the role of these modes.

Table 1. Mode share of Beijing residents.

Mode	2010 (%)	2011(%)
Bus	28.9	28.2
Subway	10.0	13.8
Taxi	7.1	6.9
Car	34.0	33.0
Bike and walking	18.1	15.1
Company shuttle	1.9	–
Other	–	3.0
Total	100.0	100.0

Sources: BTRC (2011, 2012).

Beijing Public Transportation Company (BPTC) is in charge of the public system in Beijing. As of 2011, the company has 28,343 buses on 948 bus routes with a total length of 187,500 km. In 2011 alone, these buses travelled 1.7 billion vehicle km and transported a total of 4.9 billion passengers. As of 2011, 95 percent of bus riders in Beijing swipe a smart card when boarding and alighting to pay for their fare (Long and Thill, 2015). The swipes automatically generate the following information regarding cardholders:

a. Bus trip origin and destination information;
b. Boarding and alighting time;
c. Unique card number and card type (student card at a discount vs regular card).

To increase the usage of smart cards among transit riders, BPTC has worked with other local agencies so that smart cards can also be used in the local metro system and for paying utility bills and taxi services. Currently, unless they are still within the metro system, transit riders have to swipe their cards again each time they start a new transit trip.

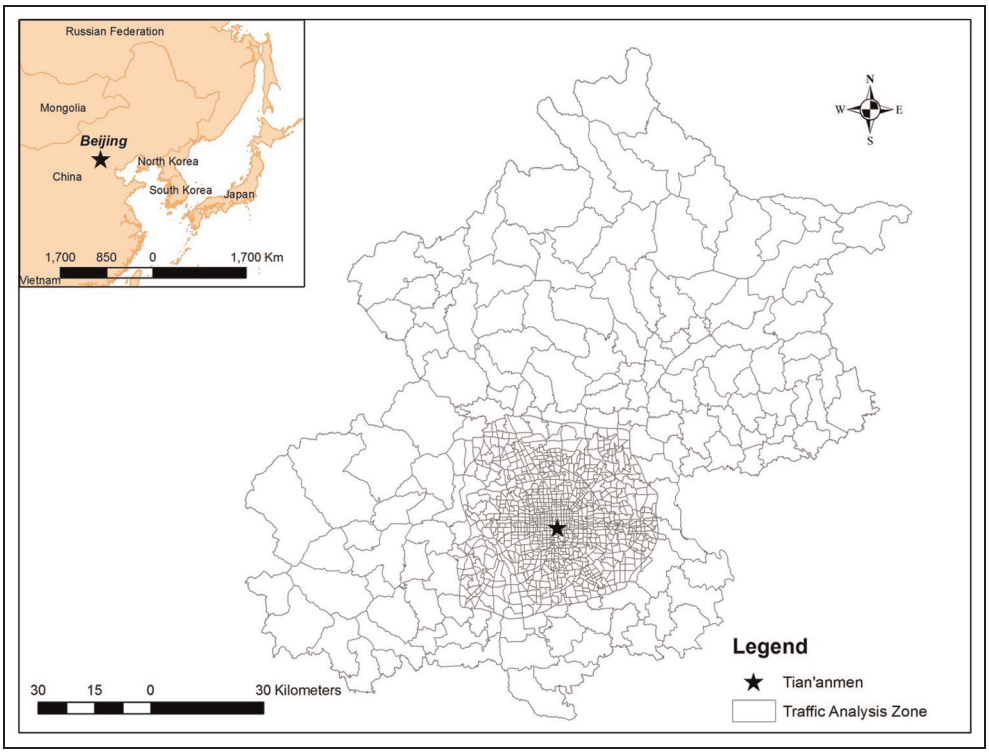

Figure 2. 1118 TAZs in Beijing.

Beijing Transportation Research Center (BTRC) is the local transportation planning agency. The BTRC is charged with collecting local travel survey data as well as developing and maintaining local travel demand models. The BTRC divides the Beijing metropolitan area into 1118 TAZs. Figure 2 is the map of these TAZs, which are the unit of analysis of this study.

In excess-commute studies, actual commuting flow (in terms of trip volumes) and cost matrices are required for the calculation of theoretical minimum commute. In our study, we were granted access to a full week's historical data from the administrator who is in charge of the bus smartcard data in Beijing. The data contain 77,976,010 bus trips of 8,549,072 non-distinct cardholder records between 7 April 2008 and 13 April 2008. Given that 95 percent of bus users are smartcard holders, the one-week sample is representative of all bus users in Beijing. To identify a cardholder's workplace and residence, we queried data on an MS SQL Server 10 based on the rules and procedures that are described in Long et al. (2012) and Zhou et al. (2014).

To ensure that we singled out commuters solely by bus, we selected only cardholders who had continuous bus swipes. That is, our study excludes multimodal public transport users (i.e. bus and subway). It is possible to get a breakdown of the swipe card data by mode (subway and bus) but unfortunately we were not permitted to access such information for this study. In total, we ended up with 216,844 distinct cardholders/workers commuting solely by bus within the study

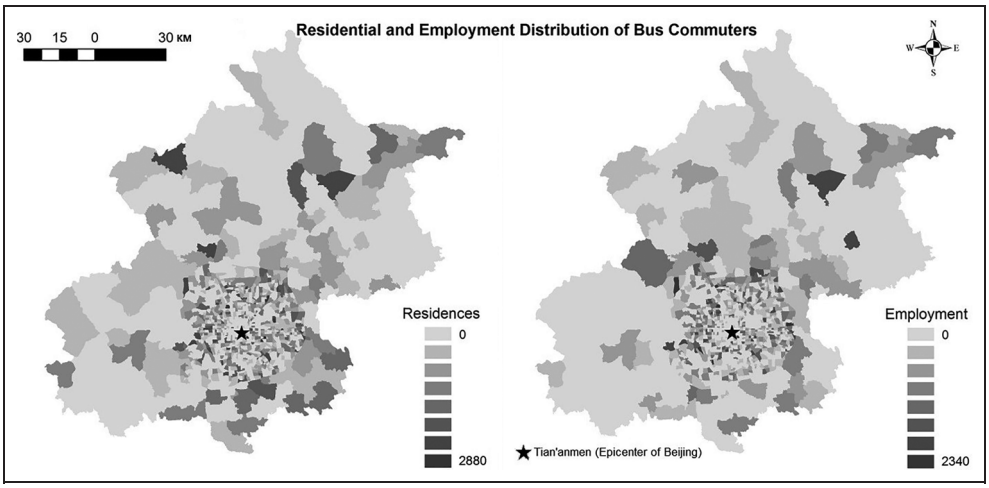

Figure 3. Distribution of bus commuters' residences and employment.

boundary (see Long et al., 2012 for more details). We then geocoded and aggregated identified homes and workplaces by the 1118 TAZs that are defined by BTRC. The spatial distributions of the residence and employment locations of the commuters/workers are shown in Figure 3. Figure 3 shows that the distribution patterns of residences and employment of the commuters are much alike, in particular in areas within a 30 km radius of Tian'anmen. This means that Beijing, especially its core, has a good quantitative balance of jobs and homes among bus commuters. After performing some simple spatial calculations, we found that the areas within a radius of 30 km to Tian'anmen have 201,765 residences and 202,212 workplaces of bus commuters in Beijing.

Methodologies

We calculated the theoretical minimum commute and associated trip distribution in Beijing based on the TPLP mentioned above, which can be expressed as the following:

$$\text{Min}: Z = \frac{1}{N}\sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}X_{ij} \tag{8}$$

$$\text{s.t.} \sum_{i=1}^{n} Xij = Dj \,\forall j = 1, \ldots, m \tag{9}$$

$$\sum_{j=1}^{m} Xij = Oi \,\forall i = 1, \ldots, n \tag{10}$$

$$Xij \geq 0 \,\forall i, j \tag{11}$$

where
Z = average transport costs;
m = number of origins;
n = number of destinations;
O_i = trips beginning at zone i;
D_j = trips destined for zone j;
C_{ij} = travel cost from zone i to zone j;
X_{ij} = number of trips from zone i to zone j;
N = total number of trips.

The objective function (8) minimises Z. Constraint (9) ensures that trip demand at each destination zone is satisfied while constraint (10) limits the number of trips leaving each origin zone to the number of trips originating there. Constraint (11) restricts the decision variables, X_{ij}, to non-negative

values. It should be noted that travel costs, C_{ij}, may be expressed in terms of any measure of zonal separation, for example travel distance, travel time or indeed a generalised cost measure. In this article, C_{ij} is measured in linear travel distance, which is a constant for a pair of origin and destination before and after optimisation. But in reality, C_{ij} can be a variable that is subject to factors such as mode choice, in-vehicle time, level of congestion, road capacity and value of time. It would be more challenging to find solutions to TPLPs when those factors are considered and when C_{ij} is a variable.

In theory, linear programming problems, including TPLPs, could have no optimal solution, indefinite optimal solutions or only one optimal solution (Winston, 2003). But for most TPLPs, they have only one optimal solution. When there is only one optimal solution, the underlying algorithm for solving a TPLP can be understood as an exhaustive trial-and-error one within the feasible region (see Winston, 2003). When there is only one solution to a TPLP, Z is minimised when the trip distribution between different origins and destinations is in a certain pattern; any other trip distribution not identical to this pattern would increase the value of Z (Charron, 2007). In other words, the only one solution to a TPLP is comparable to Pareto optimal. To simplify, this article assumes that all TPLPs in the studies of commuting have only one solution.

After implementing TPLP, we also got the optimised journey-to-work flow matrix. This matrix plus the actual commuting flow matrix are input for our calculations of the origin-specific average commute of workers living in zone i and the destination-specific average commute of workers inbound to zone j before and after the optimisation. Linking the above two matrices to Geographical Information Systems packages such as *TransCAD* 5.0 and *ArcGIS* 10.2, we successfully identified and geo-visualised the losers for both the origin-specific and destination-specific commutes by TAZ (Figure 4).

Results

Visual/map results

Figure 4, according to our knowledge, is the first of its kind in which losers in the

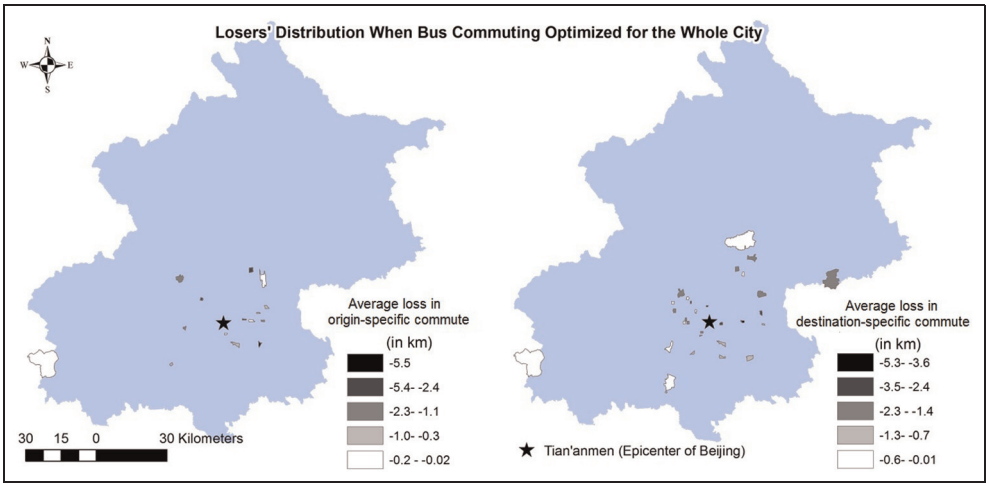

Figure 4. Distribution of the losers when bus commuting optimised.

commuting pattern optimisation are geo-coded and geo-visualised. In addition, processed smartcard data are used to produce Figure 4, which has not been done in the existing studies either. Figure 4 indicates the following:

1. Many losers concentrate in areas within 20 km east and southeast of Tian'anmen, where there is a good quantitative balance of jobs and homes, as reflected in Figure 3;
2. The TAZs that have losers in the destination-specific commute (n = 28) are more than those with losers in the origin-specific commute (n = 16);
3. Only a few TAZs (n = 4) have losers in both origin-specific and destination-specific commutes;
4. The total numbers of the TAZs (n = 44) with losers are relatively small, accounting for fewer than 4 percent of all the TAZs (n = 1118).

If we calculate the total numbers of individual losers in the origin-specific and destination-specific commutes, they are 4666 and 6129, respectively. They are also only an insignificant percentage of all the bus commuters (n = 216,844). In other words, a small percentage of workers' sacrifice in commuting distance can enable all the workers to achieve Pareto optimality in overall commuting distance. This is consistent with the modeling results of Horner and Murray (2003). Our advancements relative to Horner and Murray (2003) lie in that we not only quantify the percentage and the number of losers but also geo-visualise the location of those losers at the TAZ level. Hereafter, we call TAZs in which losers reside "loser-TAZs".

Quantitative and qualitative results. What would affect the severity of loss and spatial pattern of the losers? Enlightened by existing studies such as Giuliano and Small (1993) and Levinson (1998), we hypothesised that jobs/housing ratios in and around the loser-TAZs affect them. To test the hypothesis, we compiled Table 2.

In Table 2, for jobs and housing around the loser-TAZs, we only consider the jobs and housing of bus commuters in TAZs with their respective centroids that are within 8.1 km of the loser-TAZs. The average commuting distance of bus commuters in Beijing is 8.1 km and so we assume that bus commuters/workers are interested the most in jobs and housing within 8.1 km of their respective residences or workplaces.

Table 2. Selected attributes of the loser-TAZs.

TAZ IDs	Origin-specific commute (km)		Destination-specific commute (km)		Jobs/housing ratio in TAZ (R_i)	Jobs/housing ratio around TAZ (R_a)**
	ω_i	ω_i'	μ_j	μ_j'		
289*	7.30	9.70	4.11	4.50	0.19	1.16
301	7.77	8.10	4.24	5.10	0.09	0.90
797	5.65	8.80	1.20	2.70	0.83	1.07
1006	6.80	6.90	2.79	2.90	0.41	0.41

Notes: *There are actually 16 and 28 loser-TAZs for the origin-specific and destination-specific commutes, respectively. To save room, we show here only the four most common loser-TAZs for both commutes as examples. But when we test the hypothesis, we use all the TAZs. **Here we consider all jobs and housing in TAZs that have their respective centroids that are within 8.1 km of the loser-TAZs.

Table 3. Correlation coefficients of different pairs of variables of the loser-TAZs.

		Jobs/housing ratio		Origin-specific commute		Destination-specific commute	
		Within TAZ R_i	Around TAZ R_a	After optimisation ω_i'	Before optimisation ω_i	After optimisation μ_j'	Before optimisation μ_j
Origin-specific	ω_i- ω_i'	–0.22	0.23	–	0.3	–	–
commute	ω_i	–0.50	–0.21	0.96	1.00	–	–
(n = 16)	ω_i'	–0.50	–0.12	1.00	0.96	–	–
Destination-specific	μ_j'-μ_j	–0.20	0.25	–	–	–	0.30
commute	μ_j	0.41	–0.40	–	–	0.90	1.00
(n = 28)	μ_j'	0.23	–0.20	–	–	1.00	0.90

After identifying different attributes of the loser-TAZs, we calculated the correlation coefficients of different pairs of variables. Table 3 presents the resulting correlation coefficients.

Based on Table 3, if we use 0.5 as the cut-off value for a significant correlation coefficient, we can see that there is only strong correlation between (a) the jobs/housing ratios within TAZs (R_i's) and the origin-specific commute before and after the optimisation (ω_i' and ω_i); (b) the origin-specific commute before and after the optimisation; (c) the destination-specific commute before and after the optimisation (μ_j and μ_j'). Findings (b) and (c) are generally in line with Giuliano and Small (1993), which focus on destination-specific commute only in the Los Angeles region.

The jobs/housing ratios both within TAZs and around TAZs (R_a's) do not significantly influence the destination-specific commute before and after the optimisation. The jobs/housing ratios around TAZs do not significantly influence the origin-specific commute before and after the optimisation. The severity of loss in both the origin-specific and destination-specific commutes before and after the optimisation tends not to be correlated to the jobs/housing ratios within TAZs or around TAZs and the actual origin-specific and destination-specific commutes.

If we ignore the cutoff value of 0.5, the jobs/housing ratios within TAZs or around TAZs are negatively correlated to the origin-specific commute before and after the optimisation. The jobs/housing ratios have mixed impacts on the destination-specific commute. A higher jobs/housing ratio around TAZs reduces the destination-specific commute and a higher jobs/housing ratio within TAZs increases the destination-specific commute. The severity of loss in both the origin-specific and destination-specific commute is negatively correlated to the jobs/housing ratio within TAZs and is positively correlated to the jobs/housing ratio around TAZs.

Putting all the above together, we cannot validate the hypothesis that jobs/housing ratios in and around the loser-TAZs affect the severity of loss and spatial pattern of the losers. We only found that the jobs/housing ratios within TAZs are significantly correlated to the origin-specific commutes before and after the optimisation. In addition, either origin-specific or destination-specific commutes before and after the optimisation are significantly correlated to each other. Based on the above, we conclude that the jobs/housing balance, if measured by the jobs/housing ratio within TAZs, influences only the origin-specific commute. The severity of loss of the losers tends not to be correlated to the jobs/housing balance. The

Table 4. Selected attributes of the loser-TAZs.

TAZs	Land use	Housing	Amenities
289	Parks and lakes, established residential areas	Middle-rise apartments developed in the past 30 years or so	Parks and lakes, small restaurants and retail shops in and around the residential areas
301	Sewage plants, brown field, residential areas, warehouses and factories	Scattering middle-rise and high-rise apartments developed in the past 20 years or so	Few public facilities
797	University campus, low-cost markets and restaurants, high-end gated communities, parks and lakes	Newly developed single-family homes, long-existing farmers' homes	Parks and lakes
1006	Villages, mountains, agriculture	Long-existing farmers' homes	Mountains, trees, few public facilities

spatial pattern of the losers is largely shaped by the existing average commuting distance, as the average commute after the optimisation is positively correlated to the existing average commute.

In addition to the jobs/housing ratio, there could be other factors such as local land use patterns, employment types, housing characteristics and amenities which influence the severity of the loss among the losers and the spatial pattern of the losers. Ideally, we should secure access to as much local data as possible to investigate these factors. But such access is not easy in the Chinese context (Zhou and Wang, 2014). We therefore used data from two sources: (1) Google Earth and field trips to those loser-TAZs and adjacent areas to see what kind of land use patterns, housing options, employment and amenities there are; (2) available local employment data to examine differences in employment density between loser-TAZs and non-loser-TAZs. Table 4 presents qualitative attributes of TAZs 289, 301, 797 and 1006 based on the data from Source (1). These TAZs see loss in both the origin-specific and destination-specific commutes after the optimisation.

The land use and housing options more or less confirm why the loser-TAZs all have relatively low jobs/housing ratios within TAZs, as shown in Table 2. Except for TAZ 797, the land use and housing in TAZs do not have the diversity that transit-oriented development advocates desire. For instance, in TAZ 289, most of the apartments were built at around the same time and look alike. There is little diversity in terms of age of the building and apartment type/size. In terms of land use in this TAZ, there are only three types: residential, parks and lakes. The non-loser TAZs around them as a whole have a higher jobs/housing ratio and tend to have more diverse land use types and housing supply. Thus, they can accommodate more types of employment and possibly more incoming workers and there are also more possibilities for optimising the incoming commuting flows from elsewhere (including the loser-TAZs) where there is an oversupply of housing relative to employment. That is probably why when the commuting pattern at the global level is optimised, the non-loser TAZs could benefit more while the loser TAZs suffer in terms of their respective weighted average commuting distances.

Table 5. Employment density by industry in loser-TAZs and non-loser-TAZs.

Chinese National Industrial Classification	Average employment density (employees/km^2)		t-test for equity of means
	Loser-TAZs (n = 44)	Non-loser-TAZs (n = 1074)	Significance (2-tailed)
B. Mining	0 (0)**	11 (16)	0.005
C. Manufacturing	361 (225)	427 (535)	0.401
D. Power, gas and water supply	10 (1)	61(225)	0.001
E. Building	410 (386)	320 (283)	0.366
F. Transport, warehouse and post	200 (135)	526 (7555)	0.001
G. Information, IT and software	398 (1868)	360 (1653)	0.862
H. Retail and wholesale	622 (1557)	715 (1627)	0.641
I. Hotel*	233 (137)	361 (585)	0.285
J. Finance	70 (69)	314 (5103)	0.003
K. Real estate*	199 (112)	332 (486)	0.225
L. Rental and commercial services	460 (703)	806 (4529)	0.021
M. R&D and surveying	524 (2141)	458 (1349)	0.775
N. Water resources, environmental and public facility management	46 (4)	50 (7)	0.749
O. Residential services	102 (37)	99 (32)	0.925
P. Education	230 (204)	263 (257)	0.649
Q. Public health, social security and social welfare*	82 (14)	143 (96)	0.212
R. Public administration and social organisation*	90 (26)	170 (130)	0.159
S. Culture, sports and entertainment	108 (36)	242 (332)	0.000
All (B to S)	243 (449)	332 (1423)	0.189

Notes: * Levene's tests for equality of variances indicate that two samples have equality of variance (p-value $\leqslant$ 0.05) and so t-tests assuming equal variances are run. For the other classifications, t-tests are run assuming unequal variances.
**Variances are in parentheses.

Table 5 presents average employment density by Chinese national industrial classification of loser-TAZs and non-loser-TAZs. Levene's tests for equality in variance and t-tests for equity of means allow us to examine whether the above average employment density of the two groups of TAZs have equality of variance and equity of means. Based on the test results, we found that:

a. employment density of loser-TAZs and non-loser-TAZs in Industries I, K, Q and R have equality in variances, which means that the two types of TAZs may have similar distribution of employment density in these industries;
b. employment density of loser-TAZs and non-loser-TAZs in Industries B, D, F, J, L and S are highly likely to be from two different groups (p-value $\leq$ 0.05), where the latter tend to have a larger mean.

At this point, if we assume that employment density is positively correlated to land use, we can say that loser-TAZs dedicate a lower percentage of land to Industries B, D,

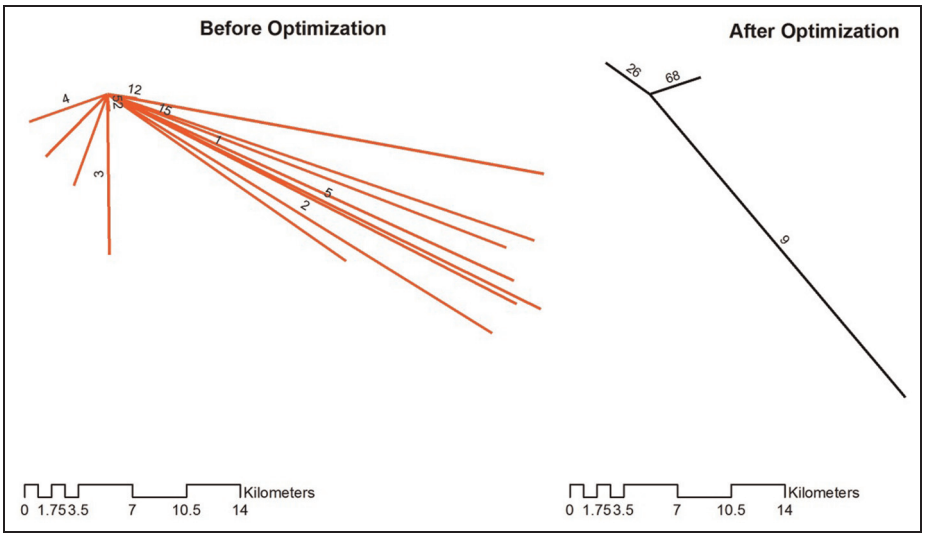

Figure 5. Commutes from TAZ 289 before and after optimisation.

F, J, L and S and dedicate a higher percentage to other industries such as I, K, Q and R. Loser-TAZs tend to have a high concentration of employment in industries such as real estate, hotels and public health/administration. This is generally consistent with the qualitative findings presented in Table 4.

Results about individual loser-TAZs. What would the commuting pattern of an individual loser-TAZ look like before and after the optimisation? To answer this, we mapped out the commuting patterns of the loser-TAZs. It is interesting that destinations of commutes from these TAZ have mostly been consolidated into a smaller number of TAZs after the optimisation. To illustrate, Figure 5 visualises the commutes from TAZ 289 before and after the optimisation.

Before the optimisation, workers residing in TAZ 289 have their workplaces in as many as 15 TAZs, including TAZ 289. After the optimisation, they commute to only four TAZs to work, including TAZ 289. To better identify losers and winners after the optimisation at TAZ 289, we made Table 6. It can be seen that the resident workers who currently commute between 4.05 and 8.1 km suffer the most after the optimisation. Most of them would have to commute between 8.1 and 12.2 km after the optimisation. In other words, the severity of the loss among the losers tends to be associated with the commute distance before the optimisation. Specifically, those who have a commute distance that is less than the average commute distance are more likely to see a higher degree of loss. In contrast, those who have a commute distance that is greater than the average commute distance are less likely to become a loser and suffer any loss. There are eight winners after the optimisation. These winners used to have an origin-specific commute that is greater than 4.05 km.

Conclusions and discussion

Existing studies have made great progress in terms of investigating the jobs/housing balance and measuring commuting efficiency from the excess-commute perspective. But few of them have paid attention to the losers, whose sacrifice makes Pareto optimality

Table 6. Commute distances of TAZ 289 before and after optimisation.

Commutedistance(km)	Number of resident workers	
	Before the optimisation	After the optimisation
<4.05	1	9
4.05–8.1	93	0
8.1–12.2	8	94
12.2–16.3	0	0
>16.3	1	0

possible for all commuters at the city or regional levels. In this article, we have expanded relevant existing studies by examining several topics related to the losers. In particular, we propose that non-zero excess commuting can be considered as non Pareto optimality and that optimising commuting patterns in the framework of TPLP where there is only one solution can be regarded as restoring Pareto optimality. We introduce the concept of "losers", develop methodologies to identify and geo-visualise the losers and examine the spatial patterns of the losers, the severity of the losers' loss and their probable influencing factors in a specific city.

Based on all the above, we obtained the following findings and implications, which we think are transferrable:

First, workers residing in individual subareas in a city or a region that have a low jobs/housing ratio could still achieve a decent average commuting distance if they search hard unilaterally. In the case of Beijing, for instance, all the four loser-TAZs have a relatively low jobs/housing ratio and an average commute that is shorter than the global average (8.1 km) before the optimisation. After the optimisation, the sacrifice of the loser-TAZs can reduce the global average commute to 3.0 km. In other words, before the optimisation, what has been done by some workers unilaterally could negatively increase the total commuting distance/cost of all the workers in the city or region as a whole, from the perspective of the system optimal. This phenomenon can be understood as losing Pareto optimality due to the unilateral behaviours of some workers, if commuting cost is the only utility we care about. It can also be comparable to the stochastic equilibrium and user equilibrium in the traffic assignment. Where some road users unilaterally change routes to improve their perceived travel times or costs, the overall travel time or cost of all road users can be suboptimal (Peeta and Mahmassani, 1995; Wardrop and Whitehead, 1952). To decision-makers and planners, this means that they should not ignore the jobs/housing ratio for any subareas in their respective cities or regions if the system optimal or Pareto optimality is their goal. There could be cases where one or two subareas with a low jobs/housing ratio can significantly increase the total commuting cost for all workers in the area. Decision-makers and planners should therefore avoid exclusionary land use and inappropriate subsidies, which could distort the land-use market, forcing workers to remote employment which can potentially be located closer to their residences (see Figure 1 and its explanations). In addition, decision-makers and planners should facilitate communications between employers and employees in terms of publicising employment opportunities. Information asymmetry can prevent employees landing a job that is closer to their residences. Of course, regardless of what decision-makers and planners

do, there could often be "fixed effects" of subtle factors that influence workers' residential and work choices, which in turn determine the severity of excess commuting, to what degree we can optimise commuting patterns, the emergence and distribution of losers and even the severity of losers' loss before and after optimisation. One example of the long-standing "fixed effects" in the US, for instance, could be "spatial mismatch" where race and related discrimination in the housing market can force workers or job-seekers to ignore some housing and/or job opportunities, even if they can reduce their commute distances (Hellerstein, et al., 2008).

Second, if we could improve or even optimise the commuting pattern in the spirit of the system optimal or Pareto optimality, there are often losers as shown in the case of Beijing. Two feasible ways to compensate these losers, according to Figure 5, is to (1) relocate as many as possible diverse employment opportunities around several traffic corridors or (2) offer transportation subsidy or faster public transportation. For a brand new city, planning jobs and housing around or along several transportation corridors, in particular public transit corridors, should also reduce the overall commuting cost as compared to letting large employers and/or developers unilaterally determine their worksites and housing sites. In reality, Copenhagen has the most employers and housing opportunities along and around its five finger-like transit corridors. The city is also famous for this and for its popularity of transit usage and bicycling.

Third, the perfect jobs/housing balance is where all commuters/workers work in a subarea where they reside or vice versa. But as shown in the case of Beijing, it is simply impossible for us to achieve such balance. For most if not all subareas (e.g. TAZs), there are always commuting trips to and from them. The jobs/housing balance of subareas, if measured by theoretical minimum commute, has different impacts on inbound and outbound commuting trips. If studies of the origin- and destination- specific commutes at the city or regional levels are challenging, policy-analysts and planners who want to promote the jobs/housing balance should at least consider such commutes at the cluster level, where there are as many as possible functionally related subareas. Simply considering a subarea's jobs/housing balance and related commuting is meaningless and could result in non-Pareto optimal, as described above.

Fourth, the diversity in land use and housing options is significantly correlated to the jobs/housing ratio. For instance, in most of the loser-TAZs in Beijing where there is a low jobs/housing ratio, there is also a lack of such diversity. In addition, we quantitatively show that employment density in selected industries in the loser-TAZs and non-loser-TAZs are significantly different. Thus, if improving the jobs/housing ratio or the jobs/housing balance is the policy goal, we need to pay closer attention to this diversity. This is also what has been advocated by other scholars such as Cervero (1989). Our studies of Beijing provide extra support of this in a brand new context. However, a high jobs/housing ratio within TAZs (R_i) or around TAZs (R_a) is not a sufficient condition of the disappearance of losers. In the case of Beijing, R_i and R_a and the differences between the origin-specific commutes (ω_i- ω_i') or destination-specific commutes (μ_j) are weakly correlated, where the two corresponding correlation coefficients are only around 0.20 (absolute value). In other words, R_i and R_a and the emergence of losers are not significantly correlated.

Despite the above findings and implications, our work can still be improved on in several aspects in the future. First, longitudinal data should be collected so that we can monitor whether losers/winners and their

respective levels of loss/gain change over time and if so, what influences them. Horner and Schleith (2012) have already explored some of these aspects (e.g. examining historical change of commuting patterns and changes of excess commuting according to socio-demographic characteristics) in the US context and have provided useful references for our future work. Second, multimodal data should be used so that we can compare losers and winners across different modes of travel. This is especially important in places where private cars and public transport fiercely compete with each other and improving commuting efficiency is vital for public transport to prevail in the competition. Third, socio-demographic and preference data about commuters/workers should be employed so that we improve not only their commuting efficiency but also their commuting experience. Last but not least, we should explore equity implications of the commuting optimisation. In this article, we focus on losers only. But there may be cases where standard deviations of the commuting length of all commuters after the optimisation become larger than the status quo. This would mean that the optimisation may have minimised the overall commuting cost but have widened the gaps in commuting costs among workers.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

References

Beijing Transportation Research Center (BTRC) (2011) *Annual report of Beijing's transportation development*. (In Chinese). Available at: http://www.bjtrc.org.cn/JGJS.aspx?id = 5.2&Menu = GZCG (accessed March2015).

Beijing Transportation Research Center (BTRC) (2012) *Annual report of Beijing's transportation development*. (In Chinese). Available at: http://www.bjtrc.org.cn/JGJS.aspx?id = 5.2&Menu = GZCG (accessed March 2015).

Boarnet MG, Hsu HP and Handy SL (2011) *Draft Policy Brief: Impact of Jobs-Housing Balance on Passenger Vehicle Use and Greenhouse Gas Emissions Based on a Review of the Empirical Literature*. Sacramento, CA: California Air Resources Board.

Buliung RN and Kanaroglou PS (2002) Commute minimization in the greater Toronto area: Applying a modified excess commute. *Journal of Transport Geography* 10: 177–186.

Cervero R (1989) Jobs-housing balancing and regional mobility. *Journal of the American Planning Association* 55(2): 136–150.

Charron M (2007) From excess commuting to commuting possibilities: More extension to the concept of excess commuting. *Environment and Planning A* 39: 1238–1254.

Frost M, Linneker B and Spence N (1998) Excess or wasteful commuting in a selection of British cities. *Transportation Research Part A-Policy and Practice* 32: 529–538.

Giuliano G (1991) Is jobs-housing balance a transportation issue? *Transportation Research Record* 1935: 305–312.

Giuliano G and Small KA (1993) Is the journey to work explained by urban structure? *Urban Studies* 30: 1485–1500.

Hamilton BW (1982) Wasteful commuting. *Journal of Political Economy* 90(5): 1035–1053.

Hellerstein JK, Neumark D and Mclnerney M (2008) Spatial mismatch or racial mismatch? *Journal of Urban Economics* 64(2): 464–479.

Horner MW (2002) Extensions to the concept of excess commuting. *Environment and Planning A* 34: 543–566.

Horner MW (2007) A multi-scale analysis of urban form and commuting change in a small metropolitan area (1990–2000). *Annals of Regional Science* 41: 315–332.

Horner MW (2010) How does ignoring worker class affect measuring the jobs-housing balance? Exploratory spatial data analysis. *Transportation Research Record* 2163: 57–64.

Horner MW and Mefford JN (2007) Investigating urban spatial mismatch using job-housing indicators to model home-work separation. *Environment and Planning A* 39: 1420–1440.

Horner MW and Murray AT (2003) A multi-objective approach to improving regional jobs-housing balance. *Regional Studies* 37: 135–146.

Horner MW and Schleith D (2012) Analyzing temporal changes in land-use transportation relationships: A LEHD-based approach. *Applied Geography* 35: 491–498.

Levinson DM (1998) Accessibility and the journey to work. *Journal of Transport Geography* 6: 11–21.

Long Y and Thill JC (2015) Combining smart card data and household travel survey to analyze jobs–housing relationships in Beijing. *Computers, Environment and Urban Systems*. In press. DOI: 10.1016/j.compenvurbsys.2015 .02.005.

AQ3

Long Y, Zhang Y and Cui CY (2012) Analyzing jobs-housing relationship and commuting pattern of Beijing using bus smart card data. *Acta Geographica Sinica* 67: 1339–1352.

Ma KR and Banister D (2006) Excess commuting: A critical review. *Transport Reviews* 26: 749–767.

Merriman D, Ohkawara T and Suzuki T (1995) Excess commuting in the Tokyo Metropolitan Area: Measurement and policy simulations. *Urban Studies* 32: 69–85.

Murphy E (2009) Excess commuting and modal choice. *Transportation Research Part A: Policy and Practice* 43: 735–743.

Murphy E and Killen JE (2011) Commuting economy: An alternative approach for assessing regional commuting efficiency. *Urban Studies* 48: 1255–1272.

Murphy E and Usher J (2013) The role of bicycle-sharing in the city: Analysis of the Irish experience. *International Journal of Sustainable Transportation*. DOI: http://dx.doi.org/10.1080/1556 8318.2012.748855.

Niedzielski MA (2006) A spatially disaggregated approach to commuting efficiency. *Urban Studies* 43: 2485–2502.

Niedzielski MA, Horner MW and Xiao NC (2013) Analyzing scale independence in jobs-housing and commute efficiency metrics. *Transportation Research Part A-Policy and Practice* 58: 129–143.

Peeta S and Mahmassani HS (1995) System optimal and user equilibrium time-dependent traffic assignment in congested networks. *Annals of Operations Research* 60(1): 81–113.

Peng ZR (1997) The jobs-housing balance and urban commuting. *Urban Studies* 34: 1215–1235.

Scott DM, Kanaroglou PS and Anderson WP (1997) Impacts of commuting efficiency on congestion and emissions: Case of the Hamilton CMA, Canada. *Transportation Research Part D: Transport and Environment* 2: 245–257.

Small KA and Song S (1992) Wasteful commuting: A resolution. *Journal of Political Economy* 100(4): 888–898.

Wardrop JG and Whitehead JI (1952) Correspondence: Some theoretical aspects of road traffic Research. *ICE Proceedings: Engineering Divisions* 1(5): 767.

White MJ (1988) Urban commuting journeys are not wasteful. *Journal of Political Economy* 96: 1097–1110.

Winston WL (2003) Operations research: Applications and algorithms. (4th edition). Boston, MA: Cengage Learning.

Zhou J and Wang Y (2014) Mobile-source GHG modeling institutions and capacities in China. *China City Planning Review* 23(2): 14–23.

Zhou J, Murphy E and Long Y (2014) Commuting efficiency in the Beijing Metropolitan Area: An exploration combing smartcard and travel survey data. *Journal of Transport Geography* 41: 175–183.