Published as: Huang, Jie, Levinson, D., Wang, Jiaoe, Jin, Haitao (2019) Job-worker spatial dynamics in Beijing: Insights from Smart Card Data. *Cities* 86, 89-93 https://doi.org/10.1016/j.cities.2018.11.021

Job-worker spatial dynamics in Beijing: insights from Smart Card Data

Abstract:

As a megacity, Beijing has experienced traffic congestion, unaffordable housing issues and jobs-housing imbalance. Recent decades have seen policies and projects aiming at decentralizing urban structure and job-worker patterns, such as subway network expansion, the suburbanization of housing and firms. But it is unclear whether these changes produced a more balanced spatial configuration of jobs and workers. To answer this question, this paper evaluated the ratio of jobs to workers from Smart Card Data at the transit station level and offered a longitudinal study for regular transit commuters. The method identifies the most preferred station around each commuter's workpalce and home location from individual smart datasets according to their travel regularity, then the amounts of jobs and workers around each station are estimated. A year-to-year evolution of job to worker ratios at the station level is conducted. We classify general cases of steepening and flattening job-worker dynamics, and they can be used in the study of other cities. The paper finds that (1) only temporary balance appears around a few stations; (2) job-worker ratios tend to be steepening rather than flattening, influencing commute patterns; (3) the polycentric configuration of Beijing can be seen from the spatial pattern of job centers identified.

Keywords: Jobs-housing balance, Smart Card Data, spatial dynamics, longitudinal analysis, urban subway network

1. Introduction

As a megacity, Beijing has experienced traffic congestion, air pollution, and unaffordable housing issues. Many residents have endured a long commute every day (Feng et al., 2008; Zhao, 2015). Many still work in the CBD where housing remains expensive, and so dwell in the suburbs where housing is more affordable. While Beijing was once a monocentric city, recent decades have seen policies and projects aiming at decentralizing urban structure and job-worker patterns. For example, a series of projects to decentralize non-capital functions included the relocation of universities and large firms (Pan et al., 2015). Policy makers have advocated commuting by public transportation to alleviate traffic congestion. For instance, sub-center construction started in the Tongzhou district in 2012, followed by the extension of Line 1 in Beijing subway system. Overall, both government-led and market-oriented projects have affected job-worker patterns in Beijing.

With the suburbanization and economic growth in Beijing, estimates of the travel time for the journey-to-work varies widely. The journey-to-work was reported at about half an hour in 2001 (Zhao et al., 2011). According to the household survey, the duration of home-to-work journey was 38 minutes in 2005 (Meng, 2009), and it was almost constant in the analysis of Smart Card Data (i.e. SCD) in 2008 (Zhou and Long, 2014). In 2010, one report even has it increasing to 52 minutes (Wang and Xu, 2010). Ta et al. (2017) reviewed jobs-housing patterns and they found that the commuting time and distance significantly increased between 2001 and 2010. However, there are few studies about job-housing patterns in Beijing since 2011.

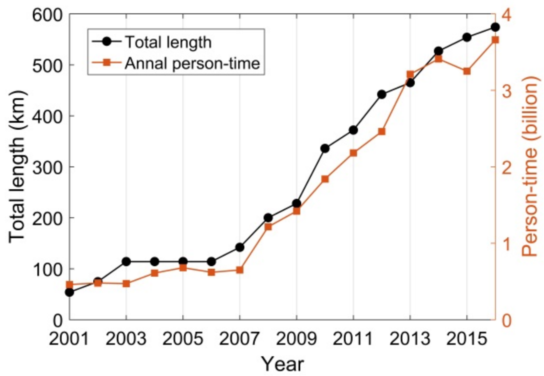

Figure 1 Total length and passengers (in person-time) in Beijing subway system from 2001 to 2015 (Data source: www.bjsubway.com).

Meanwhile, the Beijing subway system expanded rapidly between 2009 and 2015. As shown in Figure 1, the total length of subway lines nearly doubled from 228 to 554 kilometers. Between 2009 and 2011, the service areas of Beijing subway system extended to the suburbs, as many subway lines were opened: (1) Fangshan line in the southwest suburbs; (2) Daxing line from south to city center; (3) Yizhuang line in the southeast suburbs; (4) Changping line and parts of Line 15 in the north.

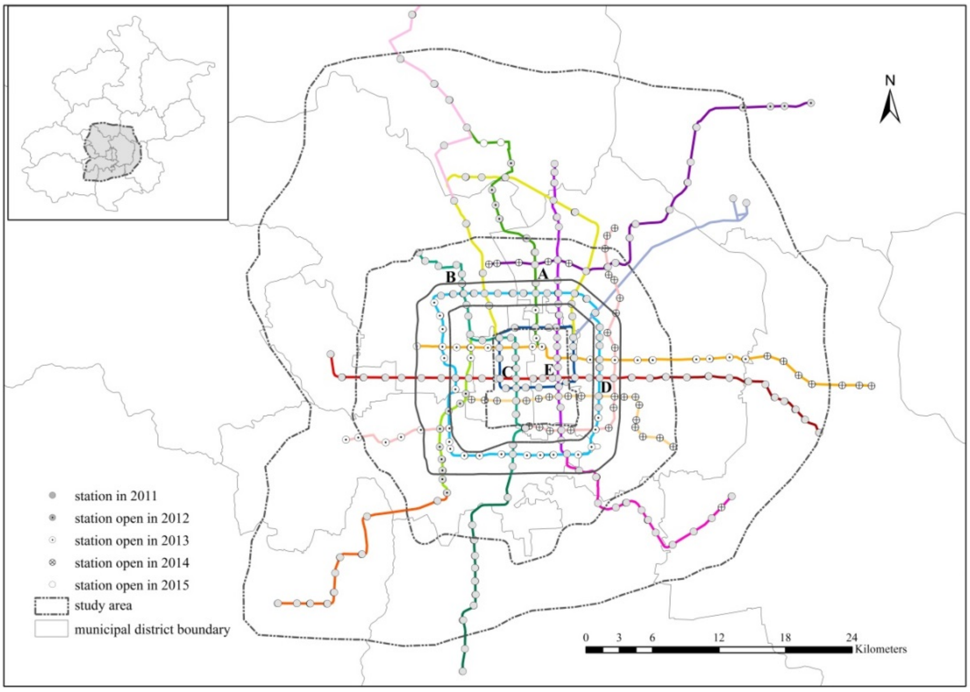

Figure 2 Network expansion of Beijing subway system from 2011 to 2015 (Data source: www.bjsubway.com; Stations labeled: A. Olympic Sports Center, B. Zhongguancun, C. Xidan, D. Guomao, E. Dongdan)

Railway lines in suburbs have connected to the network, and line density has increased since 2012 (Figure 2). For instance, Line 10, a second circle line, was completed (the first circle line is Line 2); Line 9 connected the Fangshan Line and Line 4. In 2015, the number of lines increased to nineteen. Overall, the length grew at 5.12% per annum between 2011 and 2015. The number of annual passengers grew about 0.35 billion per year between 2009 and 2012. Total passengers experienced a rapid growth from 2.46 to 3.21 billion in 2013 and a continuous increase in 2014. But the number of passengers dropped to about 3 billion in 2015.[1] As there have been few

[1] One reason behind this decrease was the growth of ride-hailing apps in Beijing. Due to the competition between

longitudinal studies on jobs-housing balance under the expansion of subway system, we focus on this issue for Beijing subway system between 2011 and 2015. With the help of smart card data, we study workers who are regular transit commuters.

Under this background, this paper contributes the following: (1) The paper conducts a longitudinal analysis of the job-worker relationship in Beijing from 2011 to 2015 at the metro station level. (2) Cases of job-worker dynamics are generally classified, including steepening or flattening variations. The remainder of this paper is organized as follow: Section 2 reviews relevant literature on jobs-housing balance and Smart Card Data, Section 3 offers the methodology; Section 4 reports results; Section 5 concludes.

2. Literature review

2.1 Job-housing Balance

The idea of job-housing balance was widely introduced by Cervero (1989), who identified institutional and zoning initiatives to synchronize metropolitan job and housing growth. 'Balance' indicates that the number of jobs is almost equal to the number of resident workers (what we call 'workers') in a given geographical area. The balanced job-housing ratio is often considered at around 1.5, assuming 1.5 workers per household (Cervero, 1989). In such case, commute distances can be shortened, the share of nonmotorized trips should increase, and energy consumption by vehicles would decrease (Murphy, 2012). Therefore, transport planners, policy makers and public agencies have advocated job-housing balance to mitigate the consequences of urban sprawl, including traffic congestion, long commutes, and associated air and noise pollution (Scott et al., 1997).

A body of literature explored factors that affect job-housing balance. The spatial mismatch may be affected by urban structures, urban sprawl, and the decentralization of employment centers or suburbanization (Dubin, 1991; Gordon et al., 1989; O'Kelly

ride-hailing apps, many commuters obtained discounts or even free rides in 2015.

and Lee, 2005). More importantly, efficient public transport services may contribute to job-housing balance by means of residential self-selection (Zhou et al., 2014). Moreover, scholars have investigated this issue in different cultural contexts. In China, high housing costs in city centers, little availability of jobs in suburbs, and housing marketization has been a source of job-housing imbalance (Zhao et al., 2011). Also, work units (Danwei in Chinese) that originated from the former Soviet Union may facilitate job-housing balance (Wang and Chai, 2009). In the United States, housing segregation by race was one reason for job-housing imbalance (Bauder, 2000; Horner and Mefford, 2007).

Furthermore, many studies tested the relationship between commuting time and job-housing balance. Based on the 'co-location hypothesis', workers tend to minimize their travel time through changing their workplace or residence, while employers also alter their firm locations in a free market (Gordon et al., 1991). Hence, a job-housing balance concerns a spatial equilibrium and shortens regional commuting time. Following this hypothesis, empirical studies found that commuting time during a rapid suburban growth may remain stable, as jobs and housing mutually co-locate to optimize travel times (Levinson and Kumar, 1994; Kim, 2008). The related notion of 'wasteful' or 'excess commuting' reflects the surplus of journey-to-work travel caused by the spatial mismatch of residence and employment (O'Kelly and Lee, 2005; Hu and Wang, 2016). Following this framework, Zhou et al. (2014) studied the gap between the theoretical minimum commute and the practical commuting patterns in Beijing.

To sum up, studies above have surveyed job-housing ratios at the metropolitan, submetropolitan, and local (neighborhood) levels (e.g. traffic analysis zones) (O'Kelly and Lee, 2005). But few have reported variation of job-housing ratios and their variations at a disaggregate level, or their dynamics. The gain or reduction of job-housing ratios may be hidden when we look at the variation at the aggregate level. Therefore, this study aims to examine the evolutionary trajectories of job-housing patterns at a disaggregate level. Also, we focus on the study of regular transit commuters instead of all social groups, which has been investigated little. We acknowledge many jobs are different and require a unique set of skills and abilities. So while an overall balance may be achieved, it does not guarantee a balance for each particular job type.

2.2 Travel regularity from Smart Card Data

In the context of big data, the spatiotemporal heterogeneity from human mobility data is useful to derive urban land use patterns, which helps urban planners and policy makers (Wu et al., 2016; Ma et al., 2017). Following this stream, Smart Card Data should present a valuable source in investigating job-housing patterns, following earlier studies using Household Travel and Activity Diary Surveys (Wang and Chai, 2009). One reason is that SCD can capture the regularity of commuters from a day-to-day analysis (Long et al., 2012; Trépanier et al. 2007). Manley et al. (2016) compared spatial-temporal patterns between irregular and regular users in the London public transport system. Long et al. (2016) investigated extreme travel behavior, such as travelling significantly early, travelling in unusually late hours, commuting an excessively long distance.

Moreover, the card type can represent some socioeconomic characteristics of transit users, such as Adult, Student and Senior Citizen. This information was used in the study of temporal variability and travel behavior (Morency et al., 2007; Legara and Monterola, 2017), inferring trip purposes (Lee and Hickman, 2014; Zou et al. 2016).

Many studies used data clustering methods. According to the unit in data mining, several levels and their linkages can be summarized as follows. Clustering smart card records to the station level has been widely used. At the station level, studies explored how built-environment affects transit ridership, commuting patterns, and spatial differences of regular transit trips (Choi et al., 2012; Long et al., 2012; Manley et al., 2016). But few studies explored job-worker relations at the station level. Then Reades et al. (2016) classified stations according to tap-in regularity of trips so that the correlation between transit demand and land use can be better understood. The observation at the station level can be extended to the regional level and then study the urban structure (Munizaga and Palma, 2012).

In the study of individual levels, whether to identify passengers through card number is a major difference in data clustering. Without passenger identification, transit trips were grouped according to similar temporal characteristics and card types, such as Morency et al. (2007) and Briand et al. (2017). With passenger identification, Ma et al. (2017) employed a spatial clustering method to investigate individual travel patterns and the method was developed from route sequences for passengers. Following this study, Zou et al. (2016) inferred passengers' home locations and Legara and Monterola (2017) captured temporal regularity of transit trips at the individual level.

Smart Card Data is useful in the study at the individual level so that the most preferred station around each commuter's workplace and home location are identified (i.e. the job station and home station). Commute mode share by transit is around 20% in Beijing, and almost half of commuters choose to travel by transit in the city center[2]. Hence, this paper suggests that Smart Card Data can be used to estimate the proportion of jobs and resident workers around metro stations. We then explore the job-worker relationship.

3. Methodology

3.1 Data Processing

In Beijing's system, each smartcard trip generates a record of both boarding and alighting stations (Ma et al., 2017). As mentioned, we prepared data from 2011 to 2015. Given that a one-week sample can be representative of a public transport system (Zhou et al., 2014), for each year, we obtained transit records for one week in April. On average, there are over 4 million trip records per day. For the study of job-housing balance, a total of over 100 million trips will be included in the analysis.

Though original data has an attribute recording card types of passengers, over 90 percent of card IDs belong to same type. Categories of card types cannot help us identify students, seniors and frequent passengers, unlike Lee et al. (2014), so we

[2] The mode share is reported by http://www.bjjtw.gov.cn/ .

cannot directly acquire socio-economic attributes or obtain commuting trips according to card types. Hence, clustering passengers according to card type is not valid for the Beijing subway system.

Instead, this paper generates an individual dataset for each card ID as shown in Figure 3. In SQL Server, we query data for each ID and collect all trips by individuals. We sort out records by weekday, summarize travel days and calculate the number of total trips for each individual. For each individual, trips are ordered by its entry time, and a trip rank is entitled correspondingly. Here, we exclude records on weekends.

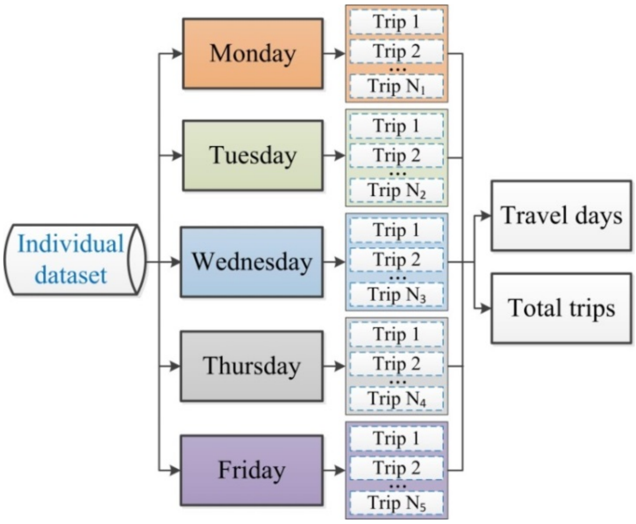

Figure 3 Structure of an individual dataset

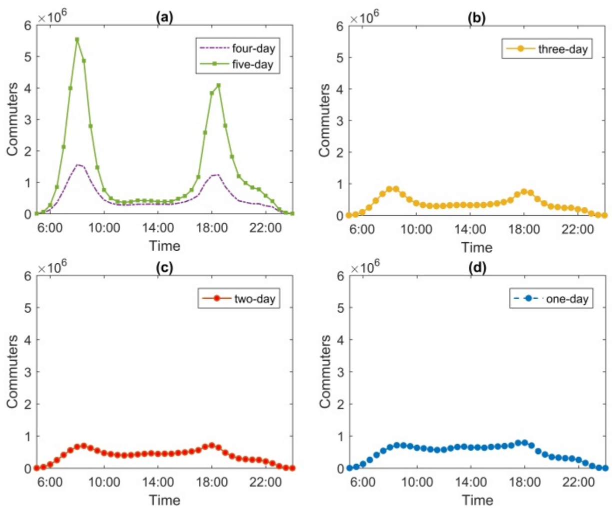

Figure 4 Temporal distribution of commuters by travel frequency (Note: the total number of boarding trips in every 30-minute interval by different commuters. For example, one-day commuters indicate those who accessed the subway system only one day in the week studied.)

3.2 Identification of job and home station

In the investigation of job-housing patterns, Zhou et al. (2014) proposed a method for the study of an urban bus system. The method sought workplaces from destination stations according to daily trips and then identified home locations based on the most frequent origin station visited. Similarly, this paper proposes a method to stations that passengers preferred to visit around their workplaces and home locations. According to the temporal disparity, entry time of four-day and five-day commuters mainly distributed during morning and evening peak hours (Figure 4). In such case, records of four-day and five-day commuters are useful in the study of job-worker balance. Therefore, one difference is that the program seeks these stations of individuals who commuted 4 or 5 days. From 2011 to 2015, the annual proportion of regular commuters rose from 23.74% to 37.37% (Table 1), and their trip records account for over 80% of transit trips.

Table 1 Statistics with smart card data

Year	Daily trips($\times 10^6$)	4-day and 5-day commuters	Card IDs
2011	3.05	981,714	4,135,115
2012	3.52	657,023	3,011,079
2013	3.77	1,273,554	4,940,565
2014	4.67	1,582,179	5,558,604
2015	4.78	1,562,899	5,710,397

Moreover, the previous method associated records with all bus stops within 500m of one another, which is within the walkable distance for commuters. However, in subway systems, the distance between two stations is usually over 1 km or even 2 km. For instance, the average distance between stations in Beijing subway system is about 1.5 km (taking about 15 minutes), which is more than typically walked for station access. Hence, another difference is that the program excludes this step. In addition, it is worth noting that the rate of school trips is few. One reason is that most students need to study at the nearest school from their home. A large number of students walk to school. For students out of the walkable regions, they are usually accompanied by parents, and they go to school by car. This paper then regards all regular commuters identified as 'workers'.

Following the process in Figure 3, each cardholder has an individual dataset. We identify the most preferred station around the cardholder's workplace (i.e. job station) based on the following rules:

(1) Access an individual dataset when the cardholder travels 4 or 5 days.

(2) Find out trips whose boarding time is 6 hours later than the alighting time of the previous trip. Namely, $B_k - A_{k-1} \geq 6$ hours, where B_k denotes the boarding time of trip t_k and A_{k-1} denotes the alighting time of trip t_{k-1}.

(3) Exclude trips if they do not occur on the same day as the previous trip. Then all remaining trips are return commuting trips for this cardholder.

(4) Among origin stations of commuting trips, the station where the cardholder visited most frequently is regarded as the job station j. The frequency of visiting the station by the cardholder is defined as f_j.

Similarly, the program identifies the most preferred station around the cardholder's home location (i.e. home station) based on the following rules:

(4) Access the individual dataset where the job station was identified above.

(6) Among destination stations of commuting trips, the station where the cardholder visited most frequently is regarded as the home station h. The frequency of visiting the station by the cardholder is defined as f_h.

It is worth noting that rules (2)-(6) were adopted from previous studies, such as (Zhou and Long, 2014; Zhou et al., 2014; Gao et al., 2018). This paper remains the time threshold '6 hours', as the *Annual Report on China Leisure Development* (2016-2017) mentioned that the average working hours was 6.03 hours in Beijing in 2016. It validates the time threshold chosen. One criterion has been added is the rule (1), as this paper focuses on the study of regular transit commuters. With the method above, this paper will identify commuters whose working hours are more than 6 hours with regular schedules and fixed workplaces.

3.3 Estimation of job-worker ratio

For each station i, we cluster the total number of individuals whose the most preferred station around their workplace is station i and whose frequency $f_j \geq 4$, and it is defined as J_i (i.e. the number of jobs at station i). With this condition, the program excludes non-regular commuters who travelled 4 or 5 days but visited various places. Also, the total number of individuals whose the most preferred station around their home locations is station i and whose frequency $f_h \geq 4$ is given as W_i (i.e. the number of workers at station i). The job to worker ratio of station i is given as $R_i = J_i/W_i$.

A question arises about the range of job to worker ratios for balanced regions. Indeed, it is not easy to achieve agreement of the range at different scales. According to the earliest definition of balanced communities, the job-housing ratio was between 0.75 to 1.25 (Margolis, 1957). Cervero (1989) suggested the upper limit should be 1.5 at the nationwide level, as there should be more than one worker per household. Peng (1997) proposed the balancing range was 1.2 to 2.8 at the scale of traffic analysis zone in the metropolitan area. However, for the study of job-worker ratio, the theoretical balance would be achieved at $R_s = 1$, as we do not consider the influence of households. Then the 'balanced' range of job-worker ratio is taken to be 0.8 to 1.2.

Following the balanced range above, other threshold values were determined

Published as: Huang, Jie, Levinson, D., Wang, Jiaoe, Jin, Haitao (2019) Job-worker spatial dynamics in Beijing: Insights from Smart Card Data. *Cities* 86, 89-93 https://doi.org/10.1016/j.cities.2018.11.021

symmetrically. For example, a ratio of 0.4 means that the number of workers is 2.5 times more than jobs within the catchment area, and a ratio of 2.5 represents the opposite relation between jobs and workers. With this strategy of differentiation, the job-worker ratios from 2011 to 2015 are shown in Figures 5(a)-(e). More details will be included in Section 4.2.

4. Results

4.1 Job-worker ratio and passenger volume

With the method in Section 3.2, a job station and a home station of each worker (i.e. cardholder k) are identified. We only exclude jobs and workers found at airport terminal stations (see Figure 2), as the regular passengers are few there. Therefore, the number of jobs almost equals workers (Table 2). In the data, the numbers of jobs and workers identified stably increased from 2011 to 2013. It rose to over 0.5 million in 2014, but decreased to about 0.3 million in 2015. It is consistent with the tendency of total annual passengers in Figure 1.

Table 2 Measured number of jobs and workers and average weighted J/W

Year	Jobs	Workers	AWR_1	AWR_2
2011	247,426	247,428	2.74	2.83
2012	250,235	250,238	2.49	2.85
2013	269, 671	269,672	3.08	3.13
2014	519,234	519,241	2.03	1.98
2015	302,387	302,394	3.41	3.35

Table 2 includes results of Average Weighted Ratio (AWR). AWR_1 is estimated with the total number of jobs and workers at each station, and it is defined as:

$$\text{AWR}_1 = \frac{\sum_{i=1}^{n}(J_i+W_i)R_i}{\sum_{i=1}^{n}J_i+W_i} \quad (1)$$

AWR_2 is estimated with the average daily trips (F_i) at each station, and it is defined as:

$$AWR_2 = \frac{\sum_{i=1}^{n}F_iR_i}{\sum_{i=1}^{n}F_i} \quad (2)$$

AWR_1 and AWR_2 are far from 1, which implies that stations with a large commuter or passengers flow tend to be job dominated. Their tendency differs slightly from 2011 to 2012. It indicated that the job-worker relation may have different influence on regular commuters and irregular passengers. Here, we focused on the study of regular commuters.

Moreover, Table 3 shows the correlation matrix of job-worker ratio and passenger flows. Overall, the boarding flow at the station level is positively related to the number of jobs, workers and their work trips. The boarding flow and job-worker ratio do not present a linear correlation.

Table 3 Correlation matrix

	Job-worker ratio	Boarding flow	Worker	Job	Work trips
Job-worker ratio	1				
Boarding volume	0.1381	1			
Worker	-0.2451	0.5562	1		
Job	0.3163	0.7232	0.1486	1	
Work trips	0.0729	0.8504	0.7169	0.7959	1

Table 4 Statistical characteristics of job-worker ratio by subway stations

Year	Stations	mean	min	max	Std.Dev.	Average travel time (mins)
2011	170	2.4551	0.0169	28.6778	4.1197	37.76
2012	180	2.7563	0.0192	39	5.2269	37.03

2013	211	2.4899	0.0100	26.1750	4.3448	37.53
2014	230	1.6427	0.0271	11.4855	1.9976	38.35
2015	266	2.4707	0.0122	38.2963	4.9373	37.98

Table 4 reports results of statistical analysis at the station level. Overall, the average travel time approximately equals that in 2005 and 2008[3] (Meng, 2009; Zhou and Long, 2014), while the average value of job-worker ratio was unstable. The minimum ratio of stations was 0.01, which indicated that the number of workers was a hundredfold more than jobs. The maximum ratio was 39, which denoted that the number of jobs was 39 times more than workers. According to the wide range, it is necessary to perform a disaggregate analysis.

4.2 Network expansion and variation of job-worker ratio

We conduct a simple spatial analysis with the function of creating Thiessen polygons in ArcGIS10.2 (Pearce, 2000). For each station, we generate its catchment area according to the location, the numbers of jobs and workers and R_s. To illustrate dynamics of J/W ratios (i.e. job-worker ratios), we generate a map of catchment areas in 2015 and retain the configuration for year-to-year analysis.

This section reviews the process how the subway network expanded and the J/W ratios of new stations. In 2012, four stations opened at the end of Line 15, and the railway line extended to the region of Ring VI. Around these stations, the numbers of residences have been much larger than jobs. Their J/W ratios ranged from 0.086 to 0.5. They formed a residential region in Northeast. Meanwhile, Line 8 connected to Changping Line, and another four stations were built. Along Line 8, one job-heavy area appeared along Ring V (J/W=7.846), while one balanced area emerged within Ring VI (J/W=1.038).

[3] Note: the average travel time estimated from Smart Card Data only include the travel time in the subway system. Including the travel time of first and last mile, the actual commuting time would be significantly longer.

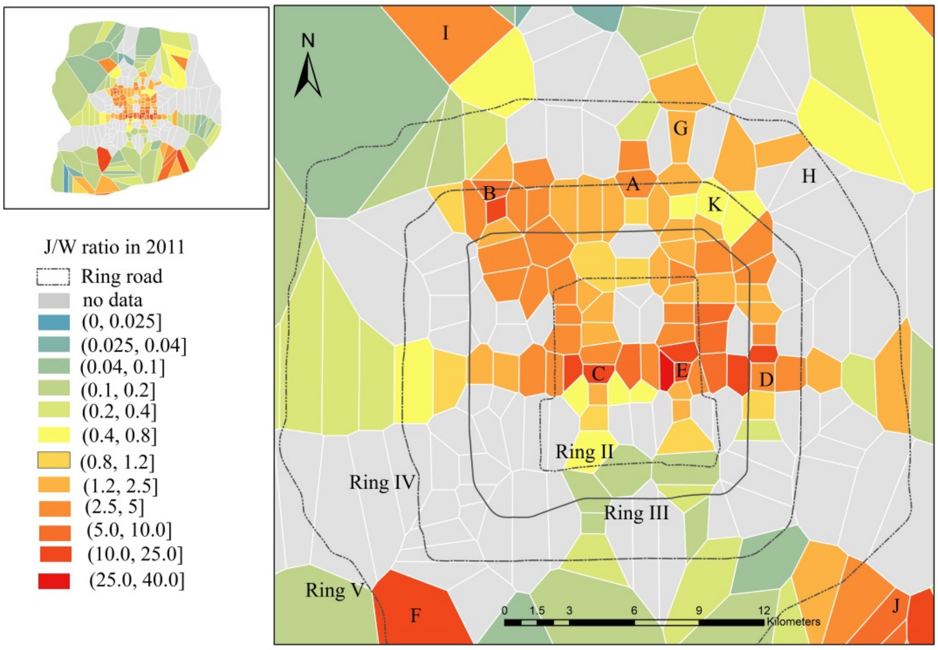

Figure 5 (a)[4]

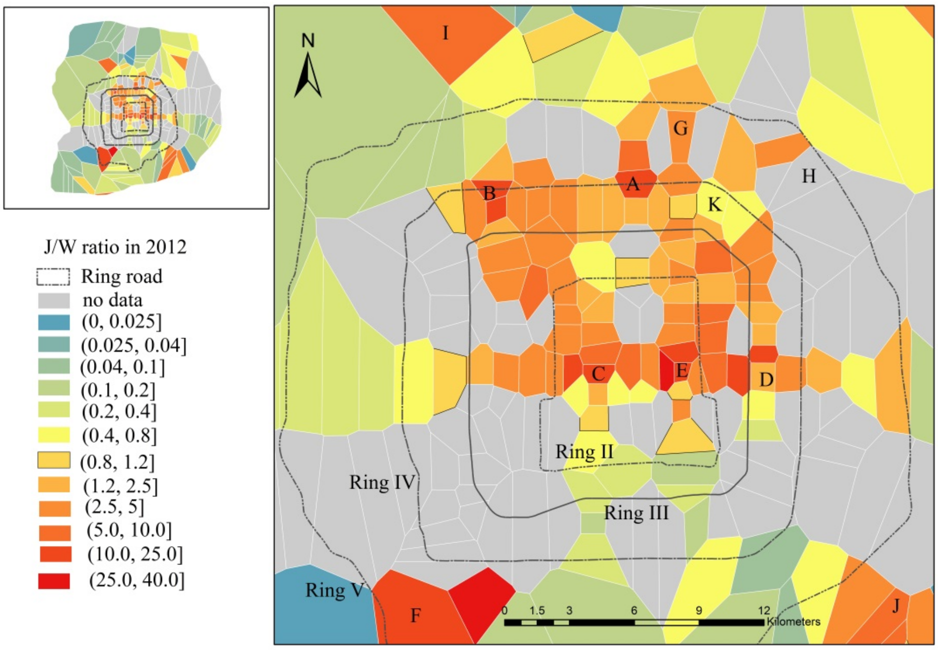

Figure 5 (b)

[4] Stations labeled: A. Olympic Sports Center, B. Zhongguancun, C. Xidan, D. Guomao, E. Dongdan, F. Fengtai Science Park, G. Beiyuan, H. Wangjing, I. Xierqi, J. Rongchang East Street, K. Huixin West Street, L. Wukesong. Following figures are labeled accordingly.

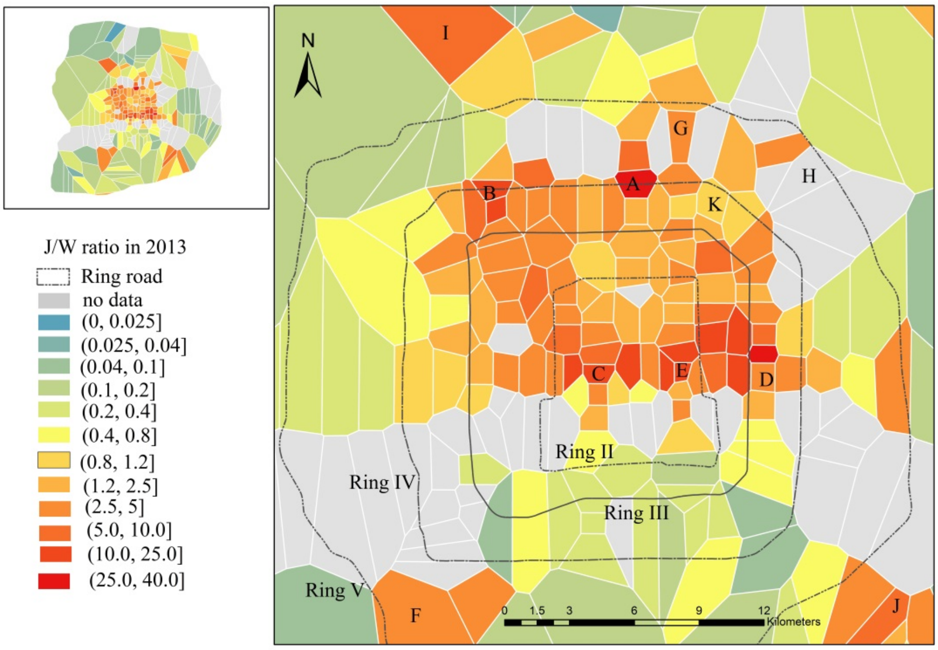

Figure 5 (c)

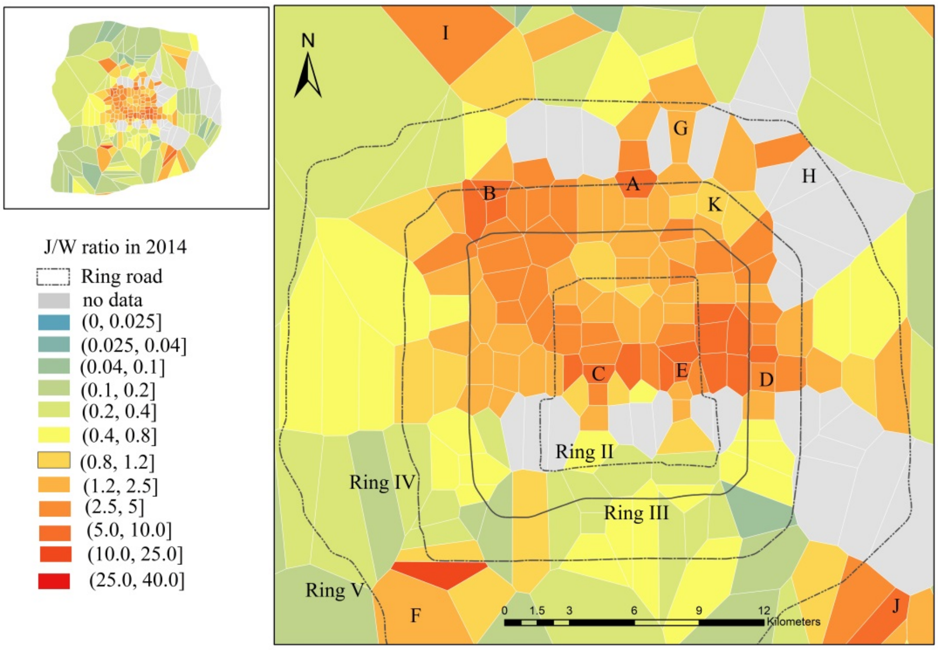

Figure 5 (d)

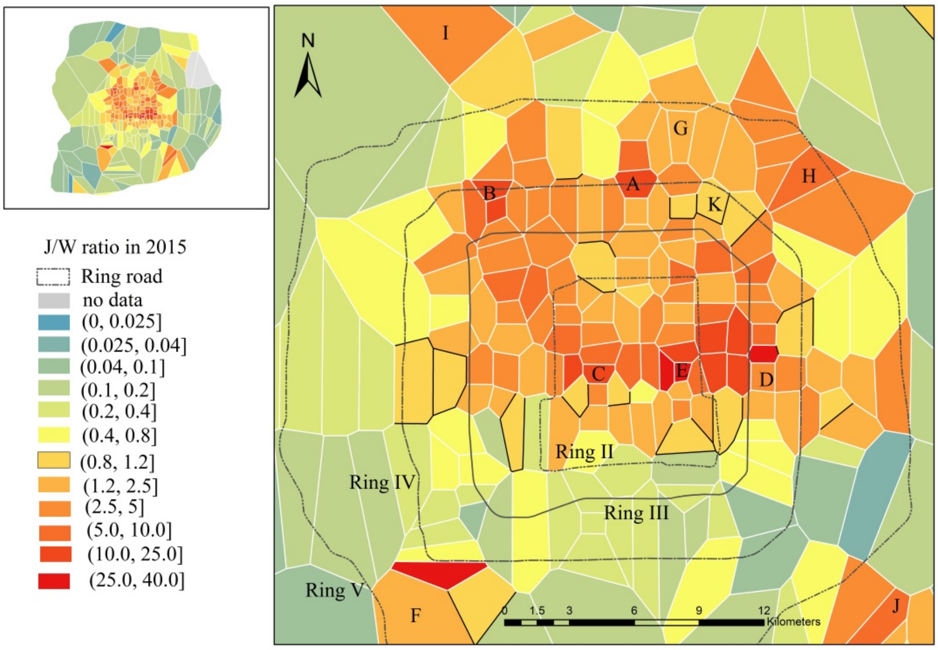

Figure 5 (e)

Figure 5 Job-worker relations from 2011 to 2015.

The major part of Line 6 was open in 2013. Around these stations, people can access more workplaces than residences around the stations within Ring III. The largest value of J/W ratio reached 12.49. However, the stations out of this region presented the opposite trend, and the smallest value of J/W ratio was 0.096. Also, Line 10 became circular, though a few stations were not yet open. These new stations generated more worker-heavy areas in the southern part of Rings III and IV. Their J/W ratios were between 0.088 and 0.6.

In 2014, Beijing subway system extended service in Fengtai district. The station density of Line 9 increased. The western part of Line 14 was constructed. Four stations on Line 10 were opened. Overall, most new stations in Fengtai district attracted more workers than jobs with a J/W ratio between 0.198 and 0.588. The only exception was Fengtai Science Park station, which has been a destination of workers.

In general, the tendency of job centers or residential regions around the new stations stayed constant in the initial stage. For instance, the four stations at the end of Line 15 remained a residential imbalance, as their J/W ratios were between 0.078 and 0.402

Published as: Huang, Jie, Levinson, D., Wang, Jiaoe, Jin, Haitao (2019) Job-worker spatial dynamics in Beijing: Insights from Smart Card Data. *Cities* 86, 89-93 https://doi.org/10.1016/j.cities.2018.11.021

the period studied. Moreover, many stations above linked suburban residences to central workplaces, such as Line 8 and Line 6. It indicates that the affordable housing issue worsened the spatial mismatch of jobs and residences. This is consistent with the finding between 2000 and 2010 (Qi et al., 2018).

4.3 Dynamics of job-worker relation: flattening vs. steepening

With an empirical study in Minneapolis and Saint Paul, Levinson et al. (2017) suggested that Twin Cities is flatter than it used to be. Following this stream, this paper proposes theoretical definitions for the flattening or steepening J/W relations. If a ratio gets nearer to 1, during the duration studied, it can be defined as a flattening case; if a ratio is farther from 1, it can be regarded as a steepening case. Moreover, it is worth to identifying areas where the job-to-worker relation varied from $\frac{J}{W} > 1$ to $\frac{J}{W} < 1$ or from $\frac{J}{W} < 1$ to $\frac{J}{W} > 1$. They can be regarded as reversing cases. The hypotheses and definitions can be summarized as Table 5 shown.

Table 5 Steepening and flattening cases in the study of job-worker dynamics

	Conditions				Definition	
Case 1	$\frac{J_1}{W_1} > \frac{J_2}{W_2}$	$J_1 > W_1$	$J_2 > W_2$	NA	flattening	job heavy
Case 2	$\frac{J_1}{W_1} < \frac{J_2}{W_2}$	$J_1 < W_1$	$J_2 < W_2$	NA	flattening	worker heavy
Case 3	$\frac{J_1}{W_2} < \frac{J_2}{W_2}$	$J_1 > W_1$	$J_2 > W_2$	NA	steepening	job heavy
Case 4	$\frac{J_1}{W_1} > \frac{J_2}{W_2}$	$J_1 < W_1$	$J_2 < W_2$	NA	steepening	worker heavy
Case 5.1	$\frac{J_1}{W_1} < \frac{J_2}{W_2}$	$J_1 < W_1$	$J_2 > W_2$	$\left(\frac{J_1}{W_1} - 1\right)^2 > \left(\frac{J_2}{W_2} - 1\right)^2$	flattening	worker-to-job reversing
Case 5.2	$\frac{J_1}{W_1} < \frac{J_2}{W_2}$	$J_1 < W_1$	$J_2 > W_2$	$\left(\frac{J_1}{W_1} - 1\right)^2 < \left(\frac{J_2}{W_2} - 1\right)^2$	steepening	worker-to-job reversing

Case 6.1	$\frac{J_1}{W_1} > \frac{J_2}{W_2}$	$J_1 > W_1$	$J_2 < W_2$	$\left(\frac{J_1}{W_1} - 1\right)^2 > \left(\frac{J_2}{W_2} - 1\right)^2$	flattening	job-to-worker reversing
Case 6.2	$\frac{J_1}{W_1} > \frac{J_2}{W_2}$	$J_1 > W_1$	$J_2 < W_2$	$\left(\frac{J_1}{W_1} - 1\right)^2 < \left(\frac{J_2}{W_2} - 1\right)^2$	steepening	job-to-worker reversing
Case 7	$\frac{J_1}{W_1} < \frac{J_2}{W_2}$	$J_1 > W_1$	$J_2 < W_2$	NA	NA	impossible
Case 8	$\frac{J_1}{W_1} > \frac{J_2}{W_2}$	$J_1 < W_1$	$J_2 > W_2$	NA	NA	impossible

For the cases mentioned above, Table 6 shows in total that 55 stations are flattening, 107 stations are steepening, and 18 are reversing (which may be flattening or steepening). Also, their spatial distribution is shown in Figure 6. The steepening tendency is consistent with the agglomeration of jobs in the city center and the increasing number of residents in the suburbs. Case 3 (steepening, job heavy) stations tend to be located within Ring IV. Case 4 (steepening, worker heavy) stations are more often in the suburbs (namely outside of Ring V).

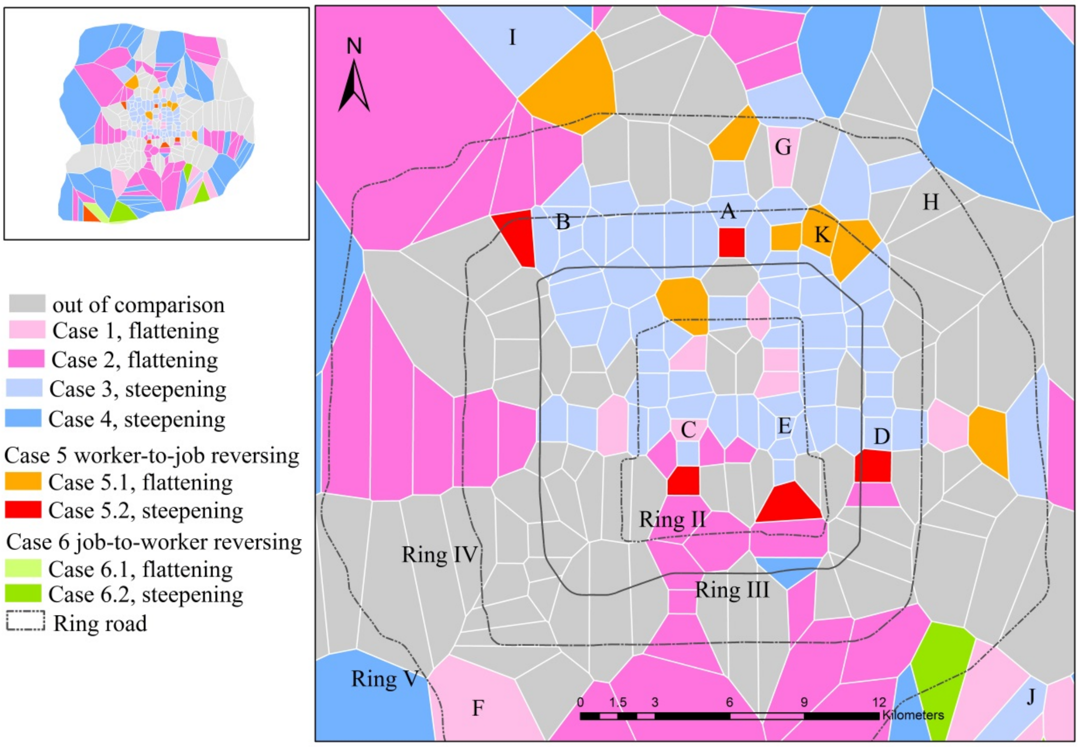

Figure 6 Spatial patterns of flattening and steepening cases between 2011 and 2015

There is not an obvious spatial configuration for flattening cases, as they scatter across the region studied. Overall, few stations within the city center have balanced job-worker ratios. Compared to the steepening cases, the flattening cases have impact upon a smaller region, and fewer job locations, but a similar number of workers. In 2015, jobs within the flattening area were only 0.05 million, while those in the steepening area were about 0.2 million.

In total, the reversing case only occurs at 18 stations. Most worker-to-job reversing stations are close to the city center. These areas strengthen the agglomeration of jobs in the central region, though 7 stations belong to the reversing and flattening cases. The job-to-worker reversing case appeared in the southern part of suburb. Once again, these variations intensify the worker-heavy trend in the suburb.

Table 6 Case tendency and their spatial distribution

Case	Stations	Spatial distribution (%)*					
		II	III	IV	V	VI	Out of VI
Case 1	13	30.77	15.38	0	23.08	30.77	0
Case 2	42	9.52	4.76	19.05	26.19	40.48	0
Case 3	64	29.69	23.44	32.81	9.38	4.68	0
Case 4	33	0	3.03	0	0	90.91	6.06
Case 5.1	7	0	14.29	42.86	28.56	14.29	0
Case 5.2	6	33.33	0	50	0	0	16.67
Case 6.1	2	0	0	0	0	50	50
Case 6.2	3	0	0	0	0	100	0

* It is estimated by stations within the Ring road over the total number of stations in the case.

4.4 Job center, residential community and balanced region

As the study via the household survey usually pre-estimated the location of job centers and residential communities (such as Wang and Chai (2009)), the survey was conducted within particular regions. Different from the household survey, the research with Smart Card Data is more quantitatively fair to compare all job centers and residential communities. Hence, it is useful to examine job centers and residential communities with the estimated job to worker ratios. Also, it ensures a continuous observation across the whole city. In such a case, the spatial dynamics can be investigated. According to the configuration of job centers, it slightly varied from a monocentric to a polycentric structure during the period studied.

Over half of jobs locate at the central region, which forms the largest job cluster within Ring IV. As J/W ratios tend to increase (Section 4.3), this region will aggregate more jobs instead of residential locations. Also, the central region attracts 60% of passenger flow. Hence, stations with a larger passenger flow tend to be job heavy areas, which is consistent with the observation of average weighted ratio (Section 4.1).

Furthermore, five sub-centers can be identified within the central region, and they are Xidan, Dongdan, Zhongguancun, Olympic Sports Center and Guomao (Table 7). Among these centers, only Olympic Sports Center did not attract abundant jobs in 2011. The spatial configuration of other sub-centers has been seen explicitly since 2011.

The emergence of sub-centers above can be explained by different strategies of urban planning. Xidan and Dongdan have been two typical sub-centers within Ring II (the inner city). Zhongguancun has been a job center gathering advanced technology companies (like a small 'Silicon Valley') since 1980s, as it was planned to be a science park. Olympic sports center gradually emerged as a business center after Beijing Olympic Games in 2008. Offices and conference and convention centers are located there. Guomao has been a business center since 2010. It is surrounded by a financial center and offices of various companies.

With suburbanization, four job centers have been constructed for the industrial agglomeration. Wangjing and Xierqi have gathered advanced technology companies. With geographic proximity, Beiyuan also attracted companies in the similar field. In addition, several industrial zones located around the station in Southeast (i.e. Rongchang East Street).

Similarly, Fengtai Science Park is a job center in Southwest (Section 4.2). As mentioned in Urban Plan of Beijing (from 2016 to 2035), Fentgtai district will construct a job center and encourage residents to work and commute within the district. With the observation here, Fengtai Science Park station should be a candidate location to contribute the job-worker balance at a local level.

Table 7 Stations selected and geographic attributes

Station	J/W (2015)	Remarks
Olympic Sports Center	12.389	Conference centers, exhibition centers and offices locate there.
Zhongguancun	18.357	A job center gathers advanced technology industry, surrounding by
Xidan	19.568	In the inner city, it gathers offices, shopping malls and entertainment
Guomao	20.362	A business center agglomerates banks and financial companies.
Dongdan	38.296	In the inner city, it gathers offices, shopping malls and entertainment
Beiyuan	2.429	It changes from a residential community from a job center with the agglomeration of advanced technology companies.
Wangjing	5.239	A job center gathers advanced technology companies.
Xierqi	4.623	A job center gathers advanced technology companies and Internet
Rongchang East Street	6.960	It is within Beijing economic and technical development zone (ETDZ).
Liangxiang University Town West	0.012	A station along Fangshan Line is surrounded by campuses and residential communities.
Gonghuacheng	0.025	A station along Changping Line is surrounded by campuses and residential communities.
Wanshoulu	0.965	A balanced region gathers companies of manufacturing industry, schools and residential communities.
Tiantandongmen	1.187	A balanced region gathers residential areas, hospitals, schools, attractions and offices.

Compared to the agglomeration of jobs, residential communities are relatively decentralized. Within Ring II, we can only find two worker-heavy areas with J/W= 0.593 and 0.77 in 2015. Also, the lowest value of J/W ratio within Ring IV was 0.084. Few residential communities emerge in the central region. Surrounding the job centers in the suburb, some catchment areas present worker-heavy tendency, and the workers are distributed evenly. In addition, stations along Changping Line and Fangshan Line show the worker-heavy tendency more explicitly; as the smallest value of J/W ratios was 0.025 and 0.012 respectively (see Figures 2 and 9).

During the years studied, stations with job-worker balance gradually increased with the network expansion. Between 2011 and 2013, the number of stations whose catchment areas balanced jobs and workers was around 10. In 2014, this number increased to 18, and it remained 19 in 2015. Only two stations remained in job-worker balance over the five years, they were Wanshoulu and Tiantandongmen. Other stations only presented temporary job-worker balance.

5. Conclusions

This paper analyzes job-worker dynamics in Beijing. Based on travel regularity, this paper proposes a research method to determine the unique job station and corresponding home station for each regular commuter. Also, we performed a spatial analysis. We define for possible variations of job-worker dynamics and test associated hypotheses. Then this paper investigates the variance of J/W spatial pattern, and the configuration of job centers and residential communities were studied. Conclusions are summarized as follow.

First, the steepening job-worker ratio significantly influenced commuting in Beijing. Compared to the flattening cases, the steepening relation affected wider areas in the city center as well as the suburb, though the overall weighted average job-worker relation was about 2.4 between 2011 and 2015. Hence, this paper emphasizes the importance of examining job-worker relation at a disaggregate level. The theoretical definitions of steepening and flattening cases are useful in the study of other cities.

Second, more station catchment areas present a job-worker balance, though we only observed temporary balance around many stations. The areas around Huixin West Street and Wukesong stations have been two largest balanced regions within Ring IV (Figure 5(e)). Across the whole city, the number of stations whose catchment areas are under job-worker balance is below 10%.

Third, compared to studies based on the survey, the study from Smart Card Data can provide a parallel analysis for all possible job centers and worker clusters. With the observation abover, we conclude that Beijing continues to evolve from a monocentric to a polycentric city. From 2011 to 2015, the spatial configuration of job centers slightly evolved into one central cluster and five surrounding centers. But the distribution of workers was relatively decentralized in Beijing. For a better job-worker ratio, one suggestion is that policy support the decentralization of job locations. In particular, more workplaces should be encouraged to move toward the suburbs where residential communities have been established recently.

Finally, it is worth noting some limits in this work. Generating catchment areas with Thiessen polygons worked smoothly in the areas of high station density but not in the areas of few stations. It may affect the analysis in the suburbs. Also, the study based on smart card data can only estimate a quarter of urban commuting in Beijing. The job-worker ratio generated by car, bus, walk, and bike needs additional observation. Moreover, this paper only investigates spatial mismatch for particular transit users with regular schedules and fixed workplaces. Many jobs are different, such as cleaners who work extremely early within a few hours, or those jobs without regular schedules. Those jobs have not been considered systematically in this paper. Future research can trace the trajectories of people who continuously access Beijing's subway system over the five years.

References

[1] Bauder, H. (2000). Reflections on the spatial mismatch debate. Journal of Planning Education and Research, 19(3), 316-320.

[2] Bin, M. (2009). The spatial organization of the separation between jobs and residential locations in Beijing. Acta Geographica Sinica, 64(12), 1457-1466.

[3] Briand, A. S., Côme, E., Trépanier, M., & Oukhellou, L. (2017). Analyzing year-to-year changes in public transport passenger behaviour using smart card data. Transportation Research Part C: Emerging Technologies, 79, 274-289.

[4] Cervero, R. (1989). Jobs-housing balancing and regional mobility. Journal of the American Planning Association, 55(2), 136-150.

[5] Choi, J., Lee, Y. J., Kim, T., & Sohn, K. (2012). An analysis of Metro ridership at the station-to-station level in Seoul. Transportation, 39(3), 705-722.

[6] Dubin, R. (1991). Commuting patterns and firm decentralization. Land Economics, 67(1), 15-29.

[7] Feng, J., Zhou, Y., & Wu, F. (2008). New trends of suburbanization in Beijing since 1990: From government-led to market-oriented. Regional Studies, 42(1), 83-99.

[8] Gao, Q. L., Li, Q. Q., Yue, Y., Zhuang, Y., Chen, Z. P., & Kong, H. (2018). Exploring changes in the spatial distribution of the low-to-moderate income group using transit smart card data. Computers, Environment and Urban Systems.

[9] Gordon, P., Richardson, H. W., & Jun, M. J. (1991). The commuting paradox evidence from the top twenty. Journal of the American Planning Association, 57(4), 416-420.

[10] Horner, M. W., & Mefford, J. N. (2007). Investigating urban spatial mismatch using job–housing indicators to model home–work separation. Environment and Planning A, 39(6), 1420-1440.

[11] Hu, Y., & Wang, F. (2016). Temporal trends of intraurban commuting in Baton Rouge, 1990–2010. Annals of the American Association of Geographers, 106(2), 470-479.

[12] Jiang, H., & Levinson, D. (2017). Accessibility and the evaluation of investments on the Beijing subway. Journal of Transport and Land Use, 10(1), 395-408.

[13] Kim, C. (2008). Commuting time stability: A test of a co-location hypothesis. Transportation Research Part A: Policy and Practice, 42(3), 524-544.

[14] Lee, S. G., & Hickman, M. (2014). Trip purpose inference using automated fare collection data. Public Transport, 6(1-2), 1-20.

[15] Legara, E. F. T., & Monterola, C. P. (2017). Inferring passenger types from commuter eigentravel matrices. Transportmetrica B: Transport Dynamics, 1-21.

[16] Levinson, D. M., & Kumar, A. (1994). The rational locator: why travel times have remained stable. Journal of the american planning association, 60(3), 319-332.

[17] Levinson, D., Marion, B., Owen, A., & Cui, M. (2017). The City is flatter: Changing patterns

of job and labor access. Cities, 60, 124-138.

[18] Long, Y., Zhang, Y., & Cui, C. Y. (2012). Identifying commuting pattern of Beijing using bus smart card data. Acta Geographica Sinica, 67(10), 1339-1352.

[19] Long, Y., Liu, X., Zhou, J., & Chai, Y. (2016). Early birds, night owls, and tireless/recurring itinerants: An exploratory analysis of extreme transit behaviors in Beijing, China. Habitat International, 57, 223-232.

[20] Ma, X., Liu, C., Wen, H., Wang, Y., & Wu, Y. J. (2017). Understanding commuting patterns using transit smart card data. Journal of Transport Geography, 58, 135-145.

[21] Margolis, J. (1957). Municipal fiscal structure in a metropolitan region. Journal of Political Economy, 65(3), 225-236.

[22] Manley, E., Zhong, C., & Batty, M. (2016). Spatiotemporal variation in travel regularity through transit user profiling. Transportation, 1-30.

[23] Morency, C., Trépanier, M., & Agard, B. (2007). Measuring transit use variability with smart-card data. Transport Policy, 14(3), 193-203.

[24] Munizaga, M. A., & Palma, C. (2012). Estimation of a disaggregate multimodal public transport Origin–Destination matrix from passive smartcard data from Santiago, Chile. Transportation Research Part C: Emerging Technologies, 24, 9-18.

[25] Murphy, E. (2012). Urban spatial location advantage: the dual of the transportation problem and its implications for land-use and transport planning. Transportation research part A: policy and practice, 46(1), 91-101.

[26] O'Kelly, M. E., & Lee, W. (2005). Disaggregate journey-to-work data: implications for excess commuting and jobs–housing balance. Environment and Planning A, 37(12), 2233-2252.

[27] Pan, F., Guo, J., Zhang, H., & Liang, J. (2015). Building a “Headquarters Economy”: The geography of headquarters within Beijing and its implications for urban restructuring. Cities, 42, 1-12.

[28] Pearce, J. (2000). Techniques for defining school catchment areas for comparison with census data. Computers, Environment and Urban Systems, 24(4), 283-303.

[29] Peng, Z. R. (1997). The jobs-housing balance and urban commuting. Urban studies, 34(8), 1215-1235.

[30] Qi, Y., Fan, Y., Sun, T., & Hu, L. (2018). Decade-long changes in spatial mismatch in Beijing, China: Are disadvantaged populations better or worse off?. Environment and Planning A: Economy and Space, 0308518X18755747.

[31] Reades, J., Zhong, C., Manley, E. D., Milton, R., & Batty, M. (2016). Finding pearls in

London's oysters. Built Environment, 42(3), 365-381.

[32] Scott, D. M., Kanaroglou, P. S., & Anderson, W. P. (1997). Impacts of commuting efficiency on congestion and emissions: case of the Hamilton CMA, Canada. Transportation Research Part D: Transport and Environment, 2(4), 245-257.

[33] Ta, N., Chai, Y., Zhang, Y., & Sun, D. (2017). Understanding job-housing relationship and commuting pattern in Chinese cities: Past, present and future. Transportation Research Part D: Transport and Environment, 52, 562-573.

[34] Trépanier, M., Tranchant, N., & Chapleau, R. (2007). Individual trip destination estimation in a transit smart card automated fare collection system. Journal of Intelligent Transportation Systems, 11(1), 1-14.

[35] Wang, D., & Xu, F. (2010). A study on the commuting problems in Beijing–based on the investigation to the citizens of Beijing. Urban Studies, 12, 018.

[36] Wang, D., & Chai, Y. (2009). The jobs–housing relationship and commuting in Beijing, China: the legacy of Danwei. Journal of Transport Geography, 17(1), 30-38.

[37] Wu, W., Wang, J., & Dai, T. (2016). The geography of cultural ties and human mobility: Big data in urban contexts. Annals of the American Association of Geographers, 106(3), 612-630.

[38] Zhao, P. (2015). The determinants of the commuting burden of low-income workers: evidence from Beijing. Environment and Planning A, 47(8), 1736-1755.

[39] Zhao, P., Lü, B., & De Roo, G. (2011). Impact of the jobs-housing balance on urban commuting in Beijing in the transformation era. Journal of transport geography, 19(1), 59-69.

[40] Zhou, J., & Long, Y. (2014). Jobs-housing balance of bus commuters in Beijing: exploration with large-scale synthesized smart card data. Transportation Research Record: Journal of the Transportation Research Board, (2418), 1-10.

[41] Zhou, J., Murphy, E., & Long, Y. (2014). Commuting efficiency in the Beijing metropolitan area: an exploration combining smartcard and travel survey data. Journal of Transport Geography, 41, 175-183.

[42] Zou, Q., Yao, X., Zhao, P., Wei, H., & Ren, H. (2016). Detecting home location and trip purposes for cardholders by mining smart card transaction data in Beijing subway. Transportation, 1-26.