

Article

Assessing the Distribution of Commuting Trips and Jobs-Housing Balance Using Smart Card Data: A Case Study of Nanjing, China

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Abstract: The purpose of this research is to assess the distribution of commuting trips and the level of jobs-housing balance with Nanjing smart card data. A new approach is presented using the Lorenz curve and Gini coefficient based on the commuting time. This article also quantifies and visualizes Nanjing's jobs-housing balance in each urban, suburban and exurban district. The core findings from this research are summarized as follows. First, the Gini coefficient of commuting time is 0.251 in urban areas, 0.258 for suburban areas and 0.267 for exurban areas. The gap of each non-urban district in commuting time is larger than urban districts. Second, the result of jobs-housing ratio (JHR) shows that jobs of Xuanwu district are far more than the working population of this district, whereas jobs and working population in other urban districts are relatively matched. The value of JHR is less than 0.8 in all suburban and exurban districts but Yuhuatai district, which suggests that jobs in these suburban districts (excluding Yuhuatai district) are in short supply compared with their working population. Third, the JHR within a particular district may be different according to the specific locations, especially those areas close to the boundary between two different kinds of districts.

Keywords: commuting trips; travel chain; public transit; jobs-housing balance; Smart card data; Lorenz curve

1. Introduction

Over the last four decades, China has experienced rapid economic growth at an average annual growth rate of nearly 10%. Meanwhile, the urbanization rate increased from 19.39% in 1980 to 58.52% in 2017. The increase in urban population is nearly 16 million each year during this period [1]. The Chinese government issued the *National New-type Urbanization Planning, 2014-2020* in 2014, which regarded the optimization of resource allocation in urban planning as one of the critical goals. Improving land-use efficiency and encouraging the construction of a public transit system have become the development direction of 'new-type urbanization.' In this background, traffic and urban planners give more attention to various public transport (e.g., metro and bus) than private motorized vehicles to deal with various diseases typical of cities, such like dense urban populations, longer commuting distance, traffic congestion and worsening air quality. Particularly considering its superiority in transportation volume, speed and punctuality, an individual would have a more satisfied and convenient experience in travel by public transportation [2]. However, the efficiency and equality of public transit have attracted little attention in China. A balanced public transit system plays an essential role in urban infrastructure due to its crucial contribution to improving individuals' access to various social, recreational and community facilities and alleviating the spatial mismatch between jobs and residential locations,

especially considering most commuters in China commute by public transit. Therefore, we need to have a thorough understanding of existing public transportation resources and commutes in China's large cities through the lens of equity.

China is experiencing the most ambitious urban rail expansions in order to meet the growing travel demand caused by rapid urban growth. Notably, the emergence of the metro has greatly enriched individuals' travel mode choice while considering the convenience and efficiency; it has undoubtedly become the best way to improve urban public transit service in metropolitan cities. By the end of 2017, 35 cities in China had metros in operation totaling 4991km, among which a total of 14 cities had more than 100 km of metro in operation. Metropolitan cities have also formed mass transit networks with metro as the backbone. Despite the explosion in metro construction, metros in many Chinese cities do not form extensive networks and a large percentage of metro riders heavily rely on bus transportation to transfer to reach their destinations [3].

The fundamental goal of public transit is supplying mobility that will benefit the whole society. However, this concept of responsibility to the public is sometimes interpreted narrowly by transit service providers and governments as providing only a minimal transit service to everyone [4]. In reality, most public transit services are concentrated in the urban and suburban due to efficiency but the distribution of population may not be consistent with this layout. This mismatching results from the imbalance distribution of costs and benefits of transport-related infrastructure and services, which may lead to worsening social inequalities and a higher threshold for individuals to move into cities [5]. That is to say, low-income and other socially vulnerable populations usually have to suffer poor quality transport and the resulting physical and time loss [6].

Since the proposal of the Spatial Mismatch Hypothesis, which links jobs with housing places, show the living condition of socially vulnerable populations in the process of reconstruction of urban space from the perspective of jobs–housing spatial relationship. Jobs–housing balance had been subjected to a great deal of study. In this connection, a typical study showed that a majority of America's black population lived in the urban area without matched fitting jobs due to the suburbanization of employment and racial discrimination in the housing market. It resulted in lower wages, higher unemployment and longer commuting distance [7]. After that, a large number of researches focus on the spatial barrier that America's black population living in urban areas have to face in terms of housing and employment opportunities [8]. Some of them extend this topic to the discussion about urban spatial inequity and its policy and institutional causes [9,10].

Concerning China, some scholars also found the separation of workplace and residence in China's major cities at different degree due to the urban sprawl and residence suburbanization [11,12]. With the construction of the geographical research framework based on the micro time of commuting trips, Chai et al. (2002) proposed that we can assess the commuting trips at short, middle and long-distance with the consideration of attributes of citizens [13]. In the case of Beijing, Li and Li (2007) found that the move of large residential quarters, like Huilongguan and Tongtianyuan, increased the extent of home–work separation, then increased the reserved time of travel [14]. Similarly, based on questionnaire surveys, Wang et al. (2011) also found severe home–work separation after the analysis of residents' commuting time and directions [15]. In addition, this separation may have different impacts on citizens with different living conditions. Notably, it may further worsen the living conditions of those with low-income, laid-off workers, migrants and other socially or physically vulnerable populations.

However, existing studies mainly focus on commuting space, commuting distance, commuting time and other factors that are affecting jobs–housing spatial separation. Furthermore, most of them are based on micro survey data target in big cities like Beijing and Shanghai. The analysis aims at home–work separation based on city-level data usually cannot reflect the specific situation and individual variation. In this situation, it is of great importance to study jobs–housing relationship at individual-level and its influence on commutes in Chinese cities. Under this background, we developed a methodology to calculate the index of distribution of commuting trips after the identification of commuters using for reference the calculation method for the Gini coefficient in the field of economics.

After that, this study quantifies and visualizes Nanjing's jobs-housing balance in each district. We apply Nanjing Smart Card Data (NSC) to assess the spatial distribution of jobs-housing based on the identification and visualization of commuters. As a kind of large-scale data with geo-tag and time-tag, smart card data has the advantage of good continuity, wide-coverage, comprehensive and dynamic information. All of these contribute to overcoming the high cost and long interval of survey data about resident trips. As mentioned above, metro as the primary public transit mode in metropolitan cities of China takes a large volume of passengers. Therefore, two different transportation modes (metro and metro-to-bus transfer) are taken into consideration in this study.

The paper proceeds as follows. Section 2 gives a review of relevant theories and studies from two perspectives. Section 3 describes the study area and data sources, then explains the construction of relevant indicators. Section 4 discusses our methodology applied to the identification of commuting trips and the assessment of home-work separation. Sections 5 and 6 present the results and discussion, conclusions and future research directions.

2. Review of the Relevant Theories and Studies

2.1. Spatial Mismatch and Commuting

Commutes reflect a concrete link between residences and workplaces and longer minority commutes due to separated home and workplace locations, at some degree, directly measure spatial mismatch. The spatial mismatch was firstly proposed due to a phenomenon in the US that African Americans lived in inner cities were separated from job opportunities in the suburbs [7]. Existing literature on spatial mismatch has been focused on the difference of commutes between minority and others [16], without the consideration of the distribution of jobs and housing. Moreover, prior studies usually put their emphasis on the analysis of influences result from the change of locations of jobs or housing on minority commutes not on how urban structure affect commuting options for different groups [17]. In this connection, some researches start to pay their attention to the distribution of cost and benefits of public transportation for different groups [18]. In the case of New York, McLafferty and Preston (1996) found that minorities tended to experience longer commuting times than non-minorities, particularly among those by public transit [19]. Similarly, based on the comparison between four Cleveland neighborhoods, Gottlieb and Lentnek (2001) found that minorities who lived in suburban areas had commutes longer than not only white suburban residents, but also than minorities from the central city [20]. Based on automatically collected transit data, Dumas (2015) found that commuters from predominantly Black or African American areas have longer travel times and slower speeds compared with those from predominantly White areas [21]. Due to the difference of the sociodemographic characteristics of neighborhoods, Wells and Till (2012) examined the existence of bias against neighborhoods with a high percentage of non-Caucasian, low-income, elderly or student residents in the aspect of bus service [22]. For the cities of China, Liu et al. (2012) found the rate of residential and employment mobility differed among different regions based on the household surveys of 2001, 2005 and 2010 in Guangzhou. That is the residents in suburban have a higher rate of mobility, while the residents in the urban core have a lower rate of mobility [23]. Besides, some extend the spatial mismatch hypothesis to the analysis of Chinese rural migrants in large cities [24]. Due to the difference in urban layout between China and western countries, most jobs, particularly blue-collar jobs, are still located in inner cities, which suggests the need for a more detailed investigation of the spatial mismatch of China's large cities.

2.2. Jobs-Housing Balance

Jobs-housing balance refers to the degree of heterogeneity in the development of urban built environment [25], precisely, the level of match between the number and type of housing and the number of jobs within a city or reasonable travel distance and time from a particular point [26]. The research on this topic based on cities in western countries assumed that workers and enterprises are all in a free

market, which will meet workers and enterprises' diverse need for residential and commercial property. A possible cause of this market failure is the limitation of planning and development management such as the racial discrimination in the household market and spatial mismatch, ultimately resulting in jobs-housing imbalance [17,27,28]. However, conditions like a free market, free will to choose residential locations and enterprises' locations, especially an efficient housing market do not exist in China. Besides, different from the car-dominated travel mode, public transit is still a significant mode for commuters in China. From this background, the goal of this study is to investigate the distribution of commutes and jobs-housing balance with Nanjing as a case study.

In addition, the traditional means used to measure the level of jobs-housing balance is calculating the jobs-housing rate, that is the ratio of the number of jobs to the number of households within a given distance [27,29]. The limitation of this means is that it is sensitive to the census tract selected, the smaller census tract selected, the less balance between job and housing. Moreover, this calculation is based on non-dynamic statistical data, so that the actual situation may be concealed then leads to spatial mismatch [30]. An individual-level analysis through the investigation of individuals' commuting distance and time, commuting mode and commuting cost will be better to help us understand the interactive mechanism between urban structure and jobs-housing pattern. In this study, individual commuter data and city-level socioeconomic data are integrated to analyze the city-specific jobs-housing balance and identifying the characteristics of commuting trips in Nanjing.

3. Study Area and Data

3.1. Study Area

As the capital of Jiangsu province, China, Nanjing has long been a policy focus of the provincial government and central government. In 2017, Nanjing accommodated a population of more than 8.2 million with an area of 6,587 km² [31]. Nanjing is located in the eastern coastal areas of China, which is one of the central cities of the Yangtze River Delta (YRD) that is a developed economic zone of China. According to the statistical yearbook, Nanjing has experienced fast growth in GDP and population since the opening and reform, accompanied by a continued increase in population density, it has reached 1,247 people per square kilometer by the end of 2017.

Nanjing is classified as a typical large city in China according to the *Standards for Categorizing City Sizes* [32] and has a relatively well-developed public transit network. In 2017, there are 369 bus lines all over the city and six open metro lines (Line 1, Line 2, Line 3, Line 10, Line S1 and Line S8), as shown in Figure 1. Its operational mileage (about 225 km) has become the 12th largest one in the world.

As shown in Figure 2, the metro network in Nanjing includes 113 stations, among which, 42 stations are located in the urban area, 34 are in located in the suburban area and 37 in exurban area. The trips by public transit account for 50% of total travel in urban areas and the number of passengers traveled by metro daily is about 2.3 million in 2016. The daily metro passengers accounted for 5.8% of public transport passengers in Nanjing in 2005 and 34.8% in 2016 and this proportion is still increasing. Considering the situation of the relatively concentrated population (Figure 2), giving priority to transit development is necessary. On the one hand, public transport utilizes land more efficiently than a car predominant society; on the other hand, this mode will allow cities to be more compact. At the same time, whether the public transit matches with this relatively concentrated population, are there any strategies to improve the level of Nanjing's jobs-housing balance, what the distribution characteristics of commutes in Nanjing? All these problems call for a detail investigation of Nanjing' jobs-housing spatial relationship.

This study defined the research scope as Nanjing City, which was divided into three kinds of areas—the urban area (including four districts, Xuanwu, Qinhuai, Gulou and Jianye), the suburban (including three districts, Yuhuatai, Pukou, Qixia) and the exurban area (including two districts, Jiangning and Luhe).

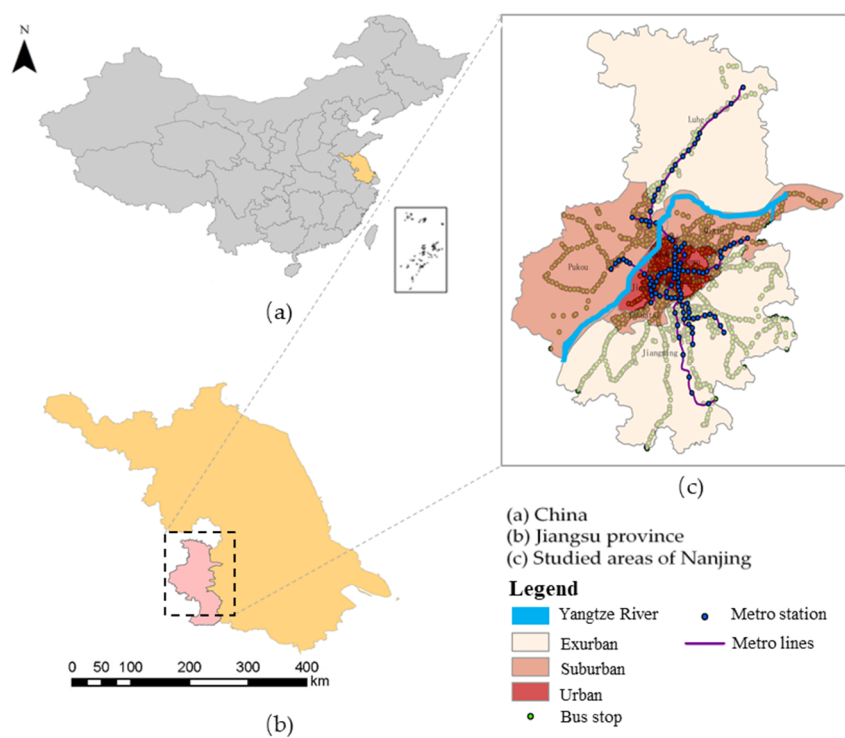


Figure 1. Study Area of Nanjing.

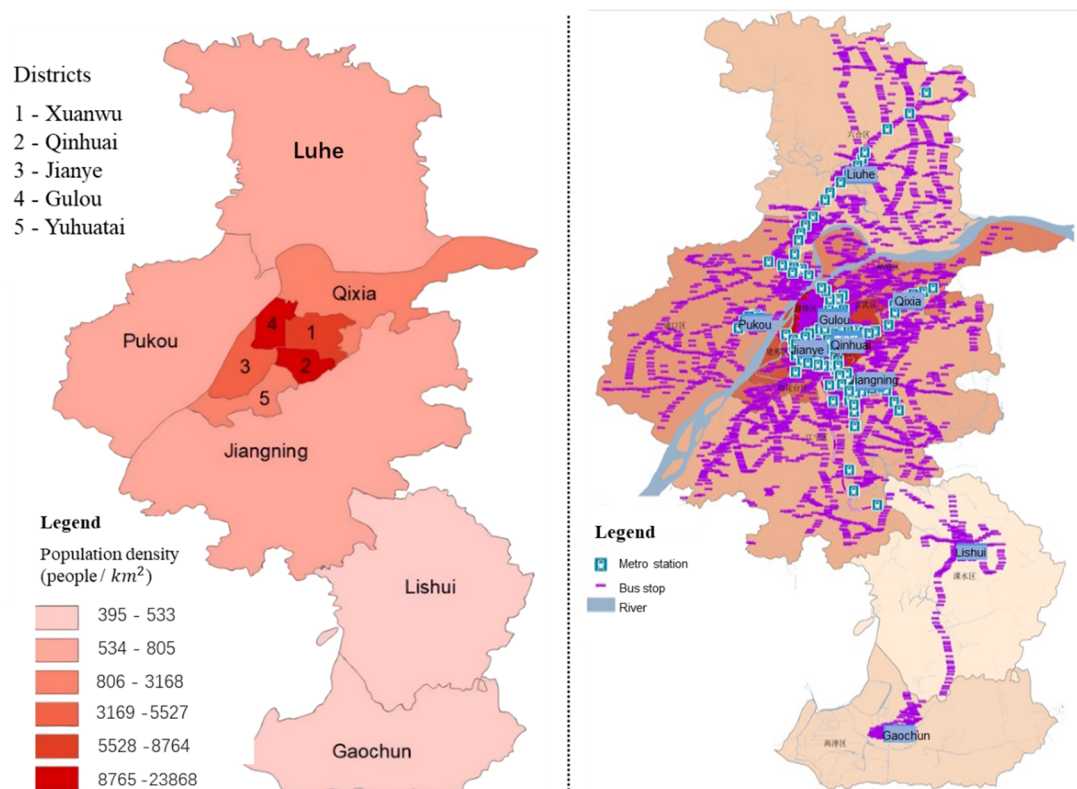


Figure 2. Resident population density and public transit distribution of Nanjing.

3.2. Data Source

Data used in this study were collected from three sources: Statistics data, Nanjing Smart Card (NSC) Data and Nanjing Point of Interest (POI) Data.

3.2.1. Statistics Data

The statistics cover data of population density and other relevant sociocultural and socioeconomic data like education and health care. The population density data came from Nanjing Bureau of Statistics [31]. Timetables and transportation time of metro lines and bus routes were acquired from the metro and bus companies, respectively [33,34].

3.2.2. Nanjing Smart Card (NSC) Data

Nanjing Smart Card (NSC) is used for the Nanjing public transit system, including metro and bus. For each smart card, its fare transaction, date, specific time, card number and card type are stored. In terms of a bus transaction, bus ID and line number are available. In consideration of our research purpose, we only extract data of working commuters. The data used in this study covered five weekdays from November 14, 2016, to November 18, 2016. The number of transactions in a typical weekday in Nanjing is about 16 to 17 million. For each transaction, several values are stored in the database. Tables 1 and 2, respectively shows a typical sequence of smart card transaction records on bus and metro generated by the public transport management system.

Table 1. Sequence of bus card transaction records.

Card ID	Transaction Date	Transaction Time	Card Type	Bus ID	Line Number
990160276059	2016/11/15	7:58:07	101	128142	106515100000
976674266424	2016/11/16	18:29:14	001	141620	101502400000
970077372367	2016/11/17	8:25:08	101	141618	101502400000

Note: (1) Card ID indicates the smart card number of each passenger; (2) Transaction Date indicates the day when the transaction occurs; (3) Transaction Time shows the time of getting on the bus; (4) Card Type contains the Adult Card, the Student Card, the Elderly Card and the Disabled Card. Card type “101” or “001” mean the Adult card; (5) Bus ID identifies the number of each bus involved in a bus transaction; (6) Line Number identifies the bus line involved in a bus transaction.

Table 2. Sequence of metro card transaction records.

Card ID	Transaction Date	Enter Station Time	Exit Station Time	Card Type	Ticket Gate ID	Metro Station Number(enter)	Metro Station Number(exit)
990160276059	2016/11/15	7:28:15	7:48:30	101	20217363	11	23
976673056780	2016/11/16	17:29:14	18:10:14	101	20069921	52	47
990164375067	2016/11/17	8:30:48	8:45:48	101	20143362	16	18

Note: (1) Enter station Time shows the time of entering the ticket gate of metro; (2) Exit station Time shows the time of exiting the ticket gate of metro; (3) Ticket Gate ID identifies the entering/exiting ticket gate involved in a metro transaction; (4) Metro Station Number identifies the entering/exiting station involved in a metro transaction; (5) The others are the same as Table 1.

3.2.3. Bus GPS Data

As the NSC system only requires bus riders to swipe their cards when they get on the bus without any information to show the specific time when they get off the bus. Based on the bus GPS location data and bus routes, we have access to the specific arriving time of each bus at a particular bus stop through matching the stop location with the electronic map and arcs offset.

3.2.4. Nanjing Point of Interest (POI) Data

Nanjing POI data, which was obtained from the Baidu map was also used in this study in order to measure the built environment. POI data is a kind of point data, representing real geographical entities and covers spatial information such as latitude, longitude and addresses. The data collected for this study includes information about the boundaries of counties and districts, urban roads, walking networks, metro stations, bus stops, residential area, working area and others. Built environment indicators were extracted from these data.

3.3. Data Pre-Processing

Figure 3 shows the whole process of transfers between metro and bus. We have access to the particular places of the transaction through the ticket gates and bus numbers. In this study, we define the metro-to-bus transfer time as the time interval between the ticket gate of the metro and the following bus-boarding. Due to the statistical difficulties, the walking time from the metro platform to metro ticket gate was not taken into consideration.

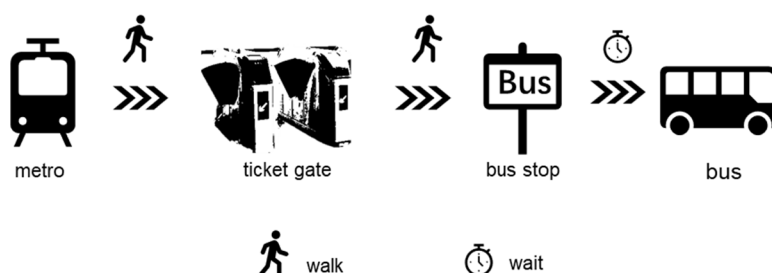


Figure 3. The process of metro-to-bus transfer.

As the NSC data does not show the details about bus-to-metro transfers directly due to the lack of touching off information of bus cards, besides the difficulties in estimating the waiting time on the metro platforms. Therefore, this study does not take the bus-to-metro transfers into consideration.

3.3.1. Integration of Bus and Metro Card Data

Firstly, we defined the individual travel chain as paired transactions, that is one metro commute followed by a subsequent bus ride or a part of a larger trip chain activity under the same NSC ID. Then we integrated metro and bus data as one complete record to present the process of an individual's public transportation trip. Table 3 shows an example of the integration of bus and metro NSC transaction records.

Table 3. Integration of bus and metro card data.

Card ID	Transaction Date	Transaction Time		Card Type	Metro Station Number	Bus line	Mode
976673056780	2016/11/15	7:28:15	7:48:30	101	11	n/a	metro
976673056780	2016/11/15	7:58:07	n/a	101	n/a	69	bus
976673056780	2016/11/15	17:05:20	n/a	101	n/a	69	bus
976673056780	2016/11/15	17:20:06	17:42:10	101	11	n/a	metro

Note: (1) Transaction time represents the time of getting on the bus, entering or exiting ticket gate of metro; (2) Mode shows the travel mode of each trip; (3) The others are the same as Tables 1 and 2.

3.3.2. Identification of Metro-to-Bus Transfer

Previous researches usually identified metro-to-bus transfers based on the maximum elapsed time between a passenger getting off a metro and then getting on a bus [35]. Most metro-to-bus transfers are made within 30 minutes [36]. Concerning the situation of London, Seaborn et al. (2009) suggested using a 20-min maximum elapsed time threshold for metro-to-bus transfers based on their travel survey data due to the negative correlation between the elapsed time threshold and the share of transfers [37]. Furthermore, some scholars recommended a 30-min criterion to exclude activities from transfers [38].

Nanjing smart card data only asks the bus riders to touch on their cards when getting on the bus without requirement of touching off when getting off. So, the bus-to-metro transfers are out of our investigation. After integrating the bus and metro data, we can identify the metro-to-bus transfers according to the transaction records documented by ticket gates at metro stations and next bus trips.

Figure 4 illustrates the frequency distribution of transfer time at every metro-to-bus transfer under paired transactions grouped by different urban and non-urban areas. In consideration of the service level of bus stations besides possible shopping and catering consumption, the adopted maximum

elapsed time threshold is set as 30 min for the observed time gaps between consecutive trip legs. Also, we find that the transaction interval time is no longer than 30 min in our sample data; therefore, this study sets the quantile at 95% (24 min) of the cumulative frequency of transaction interval time as the elapsed time threshold for metro-to-bus transfers.

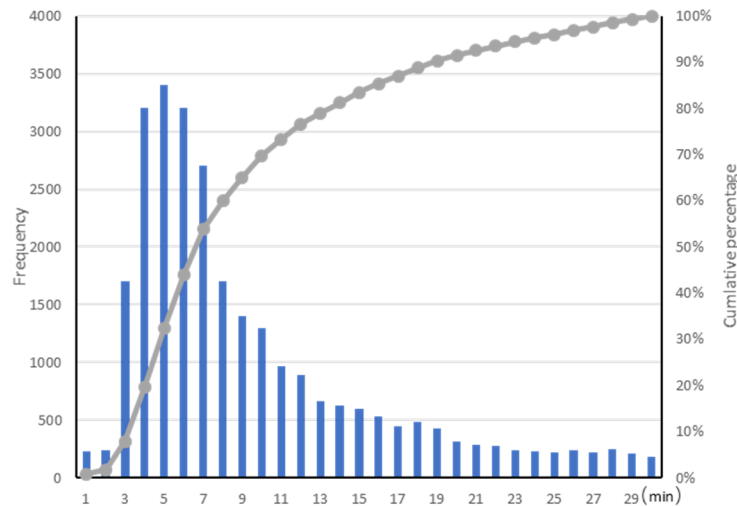


Figure 4. The cumulative frequency and distribution of different transfer times.

4. Methodology

4.1. Identifying Work Commuters

The difficulty in obtaining individual-level travel data is lower due to various intelligent public transport data collection technologies. There are many studies for the identification of commuters based on individual riders' travel data and related methods have developed maturely in the field of transportation. However, most of them focused on multi-source data fusion and the identification of commuting travel or the matching of trip departure points and destinations [39–42]. Those are all the essential steps of extracting public transit trip chain information [39,40]. Trip chain refers to a completed public transit trip comprised of one or more trip steps in sequence from the origin to the destination [39,41], existing researches on trip chain mainly focus on the type of multi-mode trip chain and influencing factors of trip mode choice [39,40]. Based on the analysis of the variation of trip time by trip chain method, Jenelius (2012) extended the analysis of travel time from single, isolated trips to daily trip chains and revealed the continuity of urban transportation trips [42]. Researches on the continuous extraction of origin-destination of the trip chain through large-scale multi-source data are still scared [40]. Furthermore, existing studies usually get the distribution of various travel modes and trip chain through a questionnaire survey, the research on trip chain about individual commuters' choice of travel mode is inadequate. This study will be a supplement to the research of the trip chain at an individual level.

In order to describe an individual's public transit process, this study also adopts the travel chain concept. Whether two connected travel behaviors constitute the transfer relationship or not depends on the transaction time interval between them under the same NSC ID. Then constructing the complete structure of each travel chain by the decomposition and combination of travelers' trip behaviors. We follow three rules applied by Ma et al. (2013) [39] and Weng et al. (2017) [40]: First, the work commutes of urban residents are characterized by the round trip, a regular interval of travel, the long interval between two swipes, fixed mode choice and various choices of public transport lines. Second, a job commuter is defined as the one whose interval between the first swipe and the last swipe is more than 7 h within a day and this situation lasts more than three days within a week. Third, due to the regular round trip of job commuters, we assumed that the destination of the first job commuting trip is close to

the origin of the following job commuting trip and the destination of the following one is close to the origin of first trip within a day. Then, the getting-off station of first travel mode, the getting-on station of the following travel mode and the transfer station between both travel modes in a travel chain can be inferred (as shown in Table 4).

Table 4. Result of a matching trip chain's origin and destination.

Card ID	Transaction Time 1	Transaction Time 2	Line 1	Line 2	Mode	Travel Chain	Step	Origin	Destination
996162086913	6:30:21	N/A	68	68	Bus	1	1	Taipingmen	Fuqiaoxi
996162086913	6:50:37	7:45:32	2	58	Metro	1	2	Fuqiao	Xinjiekou
996162086913	17:15:35	18:04:52	58	2	Metro	2	1	Xinjiekou	Fuqiao
996162086913	18:16:14	N/A	68	68	Bus	2	2	Fuqiaoxi	Taipingmen

Note: (1) Transaction time 1 represents the first transaction of each travel chain's trip step. Such as the time of getting on the bus or entering ticket gate of metro; (2) Transaction time 2 represents the next transaction of each trip chain's travel step. Such as the time of getting off the bus or exiting ticket gate of metro; (3) Origin shows the bus stop or metro station of origin; (4) Destination shows the bus stop or metro station of destination; (4) The others are the same as Tables 1 and 2.

After the identification of work commuters, their residential and working places will be recognized respectively as the origin of the first trip and the origin of the last trip within a weekday by default.

4.2. Lorenz Curves of Commuting Time in Nanjing

The Lorenz curve is widely used as a convenient graphical method to summarize income and wealth distribution information to analyze wealth inequality in economics [43]. It represents the degree of inequality in the distribution of income; an example of a Lorenz curve of population and income distribution is showed in Figure 5. The Gini coefficient is a ratio of the area between the line of equality (the dashed line in Figure 5) and the Lorenz curve (area A in Figure 5) and the total area under the line of equity (the sum of area A and B in Figure 5). The value of it will fall between 0 (representing total equity) and 1 (representing total inequity). According to international practice, a value less than 0.2 indicates perfect equality, a value between 0.2 and 0.3 indicates relative equality, a value between 0.3 and 0.4 suggests relative rationality of income gap, a value between 0.4 and 0.5 imply serious income disparities and when this value reaches more than 0.5, an excessive income inequality occurs. The smaller the degree of income inequality is the smaller the radian value of the Lorenz curve (a smaller radian value suggests the Lorenz curve will be closer to the line of equality, which means area A in Figure 5 will be smaller), then the smaller the Gini coefficient is and vice versa [44]. So, we can mathematically compare the distribution of two different Lorenz curves. The Gini coefficient is complex in mathematical calculation, it can be obtained by the following equation:

$$G = 1 - \sum_{k=0}^n (X_k - X_{k-1})(Y_k + Y_{k-1}) \quad (1)$$

where X_k is the cumulated proportion of population, for $k = 0, \dots, n$, with $X_0 = 0$, $X_n = 1$ and Y_k is the cumulated proportion of the individual accessibility variable, $Y_0 = 0$, $Y_n = 1$.

This framework can be extended to not just income but any situation that involves accumulated quantity across a population [45]. It can give a clear visual representation of equality, based on which the Gini coefficient is calculated through a single mathematical metric. Any research topic that involves quantity that can be cumulated across a population could use Lorenz curves to show the degree of inequity directly, it can be found in a range of disciplines, transport is one of them [46]. Some scholars use it to measure transit equality and found its effectiveness in reflecting the overall degree of inequality [47,48]. Based on the prior related researches, this study uses it to reflect the overall distribution of Nanjing's commutes so as to have a holistic understanding of the commuting characteristics of Nanjing.

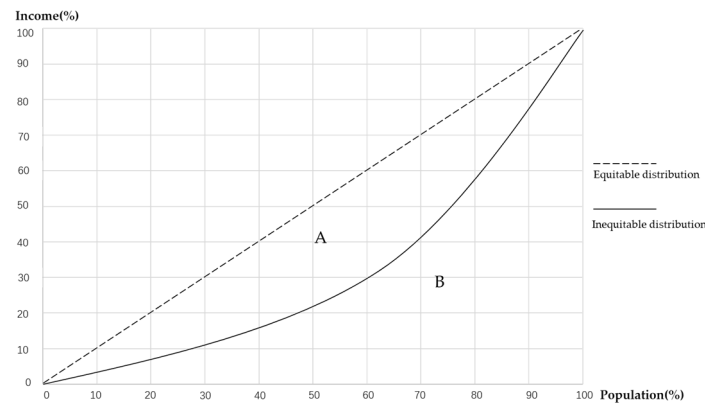


Figure 5. An example Lorenz curve.

5. Results and Discussion

5.1. Descriptive Analysis of Overall Commuting Trips

The daily work trip patterns of smart card users can be described through the weekday smart card data. Moreover, the daily trips of work commuters can be identified with the identification methods mentioned above. The distribution of identified commuters' work trip by metro or metro-to-bus transfer during five weekdays is shown in Figure 6. The letter 'B' means the bus mode and the letter 'M' refers to the metro mode. 'M+' means work trips by metro only, that is taking metro one time or more without any bus trips within a day, 'MB' means experiencing metro-to-bus transfers.

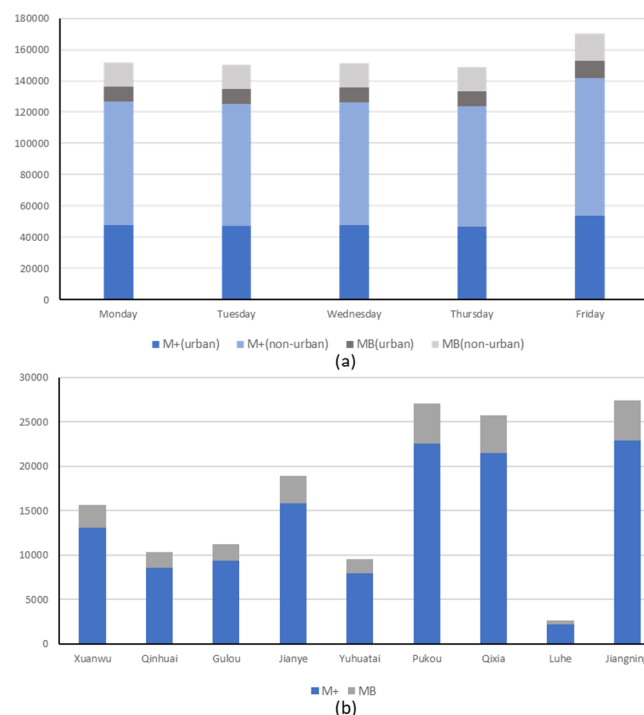


Figure 6. (a) Distribution of average number of daily work commuting trips in urban and non-urban areas (suburban and exurban areas) of Nanjing; (b) Distribution of average number of daily work commuting trips.

As shown in Figure 6, the average number of work commuters' trips in Nanjing on a weekday is about 0.153 million trips, the average number of trips by metro (not including bus) is about 0.114 million trips the average number of metro-to-bus transfer trips is about 30 thousand trips.

The urban area includes four districts (i.e., Xuanwu, Qinhuai, Gulou and Jianye) and the suburban area includes three districts (i.e., Yuhuatai, Pukou, Qixia) and the exurban area includes two districts (i.e., Jiangning and Luhe). The distribution of commuters in different districts shows different characteristics. As a whole, there are more work commuters in suburban and exurban areas than in urban areas who commute by public transit. Among urban areas, work commuters by public transit concentrate in Jianye, this is partly due to the fact that it is one of the financial centers in eastern China and is where the Hexi CBD of Nanjing is located. In addition, most work commuters by public transit appear in Pukou among suburban areas of Nanjing. It is because Pukou district is located close to the urban areas and three railway lines have been in operation there. Therefore, residents in this district may have higher metro accessibility than those in other areas. As two exurban districts, Jiangning's commutes are much more than Luhe. This is because the former is the location of several science and education parks like Jiangning campus city, which offer more potential jobs. Moreover, only one metro line is operating in Luhe while three lines in Jiangning. This difference to a large extent restricts individuals' commuting mode choice. However, Lishui and Gaochun have no metro in operation during the period of this study, so the distribution of commutes in both districts is not available.

5.2. Distribution of Commuting Trips by Public Transit in Metropolitan Area of Nanjing

In this part, we will provide a detailed comparison of the commuting distribution in each district of Nanjing by the Gini coefficient. The Gini coefficient for the overall area of Nanjing is 0.275, as shown in Figure 7. In practical terms, this means the commuting time in Nanjing is relatively uniformly distributed. That is to say, most commuters share similar commuting time.

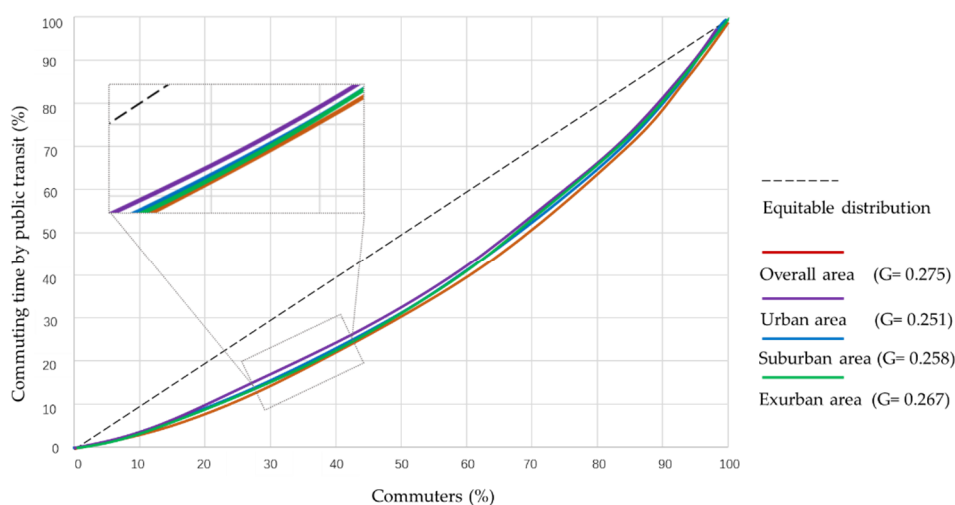


Figure 7. Lorenz curves of commuting time in the overall area, urban area and non-urban area.

The Gini coefficient of commuting time is 0.251 for the urban areas, which is slightly lower than 0.258 for suburban areas and 0.267 for exurban areas, as shown in Figure 7. This, at some degree, shows the imbalance of jobs-housing distribution is worse in non-urban areas than urban areas in Nanjing due to the unequal distribution of jobs. So, the proportion of long-distance commutes is higher in suburban and exurban districts compared with urban districts. Specifically, the Gini coefficients of all urban areas are within the normal range (between 0.2 and 0.3), as shown in Figure 8a. Among them, the Gini coefficient of Jianye district and Xuanwu district are relatively lower (as shown in Table 5), accompanied by an average travel time of 33.5 min and 32.7 min respectively. Following by Gulou district and Qinhuai district, with an average travel time of 34.4 min and 31.0 min respectively. There is little gap among these districts in average commuting time. As most economical, political and education resources centralize in these districts, residents in these areas usually do not need to work in other districts. Besides, they have access to better transport infrastructure that is also conducive

to reducing the travel time, then the distribution of commuting time becomes more even. The Gini coefficients of urban areas and suburban areas are similar, which suggests that suburban districts benefit from the spillover effect of various public facilities and economic resources. These are conducive to improving these districts' commuting conditions and creating more employment opportunities. In terms of exurban districts, this spillover effect is not significant.

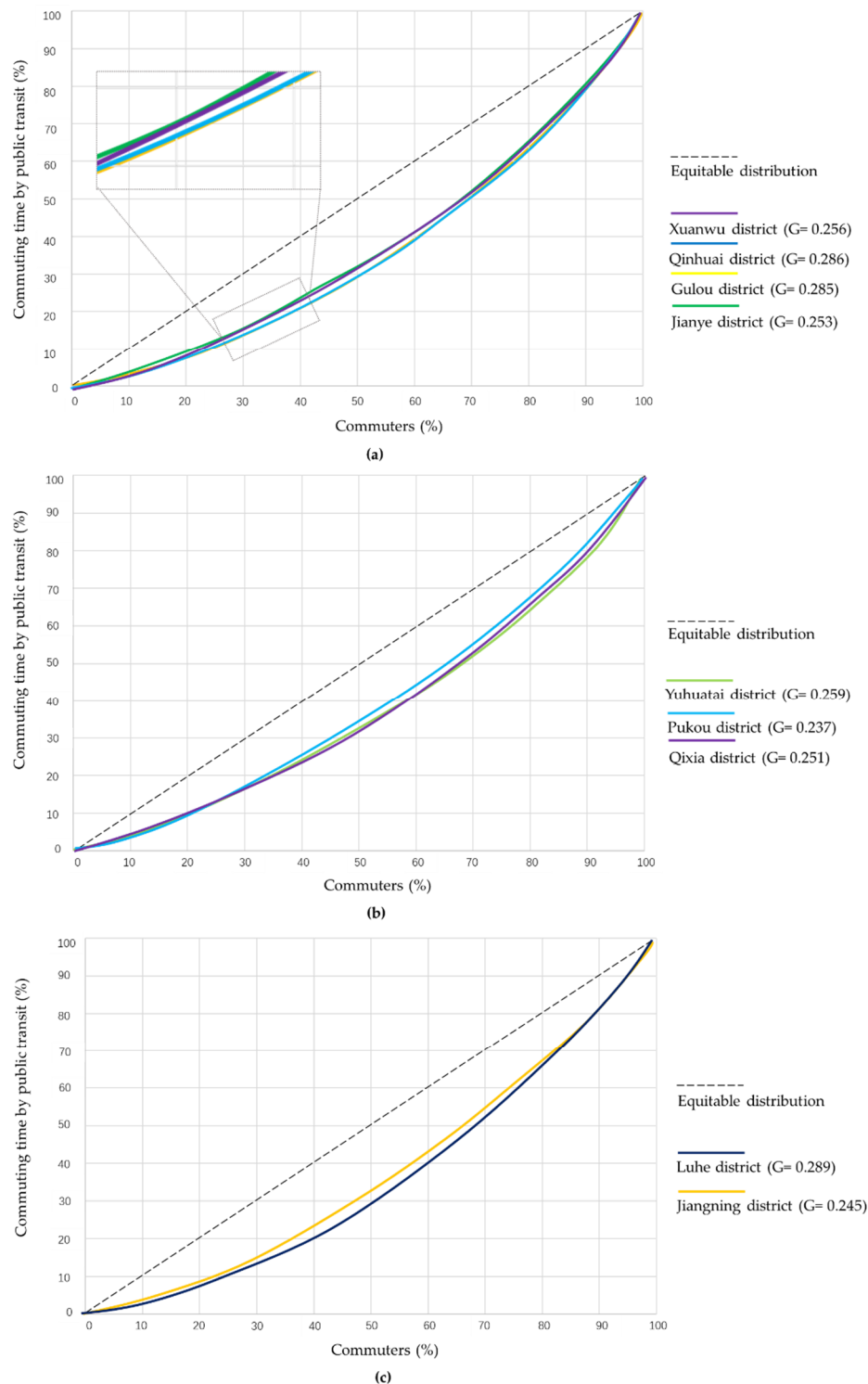


Figure 8. (a) Lorenz curves of commuting time of each district on the urban area; (b) Lorenz curves of commuting time of each district on the suburban area; (c) Lorenz curves of commuting time of each district on the exurban area.

Table 5. Average commuting time and Gini coefficients of each district of Nanjing.

Name	Gini	Time (Min)	Rank in Commuting Time
Qinhuai	0.286	31.0	1
Xuanwu	0.257	32.7	2
Jianye	0.254	33.5	3
Gulou	0.286	34.4	4
Urban	0.251	32.9	
Yuhuatai	0.259	30.7	1
Qixia	0.248	38.2	2
Pukou	0.228	44.1	3
Suburban	0.258	37.7	
Jiangning	0.257	41.3	1
Luhe	0.289	53.5	2
Exurban	0.267	47.4	

Compared with urban areas, the gap of each non-urban district in commuting time is larger. The Gini coefficient of Pukou district is the smallest one among non-urban districts. As demonstrated before, Pukou district is located close to the urban area and there are three metro lines in operation there. Therefore, residents in this district may have higher metro accessibility than those in other non-urban areas. Albeit the average commuting time by public transit in this district is about 34.061 min, which is significantly longer than other urban districts. The next one is Jiangning district, its Gini coefficient is 0.257, its relative shorter averaging commuting time is due to the following reasons: First, although it is an exurban district, its location is close to Qinhuai district (one of the urban districts), enjoying more spillover effects of transport infrastructure than some suburban districts. Second, it is the location of science and education industrial parks and Nanjing international airport, which lead more public traffic resources to incline to this district, for instance, the opening of metro line 3 that runs through the whole district and the construction of Jiangning campus city. The average commuting time of residents from Yuhuatai and Qixia is about 30.7 min and 38.2 min that rank first and second shortest time in suburban areas respectively, which are similar to urban districts. Although the reasons that lead to their good performance in travel time are different. As for Qixia district, it is an important logistics hub, sub-business center, industrial zone and a center of technology and education of Nanjing. There have been two metro lines in this district. For Yuhuatai, it is often known for its tourist attractions that demand better transit, so four metro lines are running in it. These favorable factors of transport infrastructure contribute to a short commuting time. In addition, Luhe's Gini coefficient is the biggest (0.289), which indicates that the commuting time of workers living in this district has the most uneven distribution. As the northernmost district of Nanjing, only one metro line is operating in this district. Moreover, the direct metro from Luhe to downtown is not available. All of these lead to the longest average commuting time (53.5 min), which, at some degree, suggest a low level of jobs-housing balance. Unfortunately, there is no metro lines in operation in Lishui and Gaochun during this study period, so their average commuting times are not available.

5.3. Jobs-Housing Balance of Nanjing

According to the statistical yearbook of Nanjing, Nanjing's employees of the secondary and tertiary industry reached 2.05 million in 2016 accompanied by the resident population of 6.58 million whereas the number of the resident working population is not available in the yearbook due to the limitations of data.

In order to depict the detailed situation of jobs-housing balance, we adopt the concept of jobs-housing ratio (JHR) proposed by Cervero (1989) to show the matching degree between jobs and working population within a district [29]. As JHR can be estimated from the ratio of jobs to working population, this study adopts the number of commuters whose destinations are all located in a particular district to represent the number of jobs within this district, meanwhile, we adopt the

number of commuters whose origins are all located in the same district to represent the number of working population of this district. Although the commuting data used in this study does not cover those who commute by non-public transit, in view of China's practical conditions that most commuters choose public transit as their preferred mode of transportation, the result of this study is representative and credible.

According to Cervero (1989), the value of JHR between 0.8 and 1.2 suggests a high level of jobs–housing balance, a value more than 1.2 indicates the surplus of jobs in this district and a value less than 0.8 means insufficient job opportunity. Table 6 shows that Xuanwu district's proportion in jobs of the whole city is about 33%, while its proportion in working population of the whole city only is only 11%, the JHR is up to 3.1. These results indicate that the jobs of this district is far more than the working population of this district. The JHR of other urban districts are close to 1.2, which suggest that the jobs and working population in these districts are relatively matched. In terms of suburban districts, this situation is not very well. The value of JHR is less than 0.8 in all suburban districts but Yuhuatai, which means the existence of insufficient job opportunity in these districts. This mismatch is more serious in Pukou (as shown in Figure 9), the disparity between outflow and inflow of commuters is wider. Similarly, Qixia also faces the same situation. Among exurban districts, Jiangning also faces serious lack of jobs and this is partly because its largest proportion in working population of the whole city (18.465%), there is no enough jobs to meet them although it is famous for its science and education industrial park and campus city.

Table 6. Spatial distribution of jobs and residences in Nanjing.

Location	Name	Ratio 1 (%)	Ratio 2 (%)	JHR
Urban	Xuanwu	10.532	33.151	3.096
	Qinhuai	6.953	10.830	1.532
	Gulou	7.576	13.937	1.810
	Jianye	12.762	13.876	1.070
Suburban	Yuhuatai	6.421	11.500	1.762
	Pukou	18.192	2.584	0.140
	Qixia	17.324	4.375	0.248
Exurban	Jiangning	18.465	8.769	0.467
	Luhe	1.775	0.977	0.542

Note: ratio 1 represents a particular district's proportion in working population of the whole city, ratio 2 represents a particular district's proportion in jobs of the whole city.

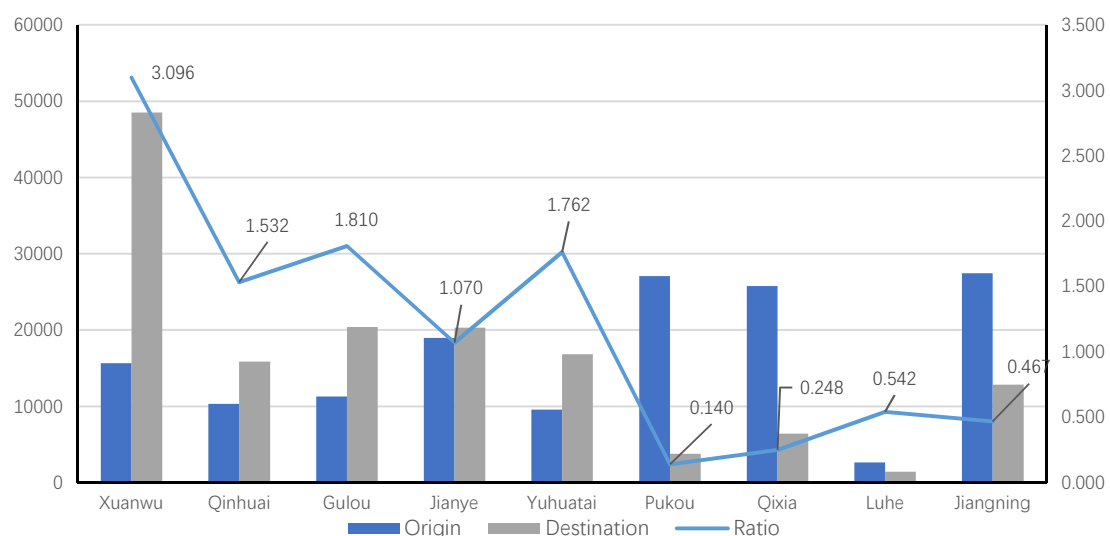


Figure 9. The number of inflow and outflow of commuters in each district.

Although jobs are also in short supply in Luhe and its JHR is close to Jiangning's, the mismatch between jobs and residential places may not vary severe due to its smaller proportion in working population and jobs of the whole city.

Note: origin represents the number of commuters whose origins of commutes are located in the particular district; destination represents the number of commuters whose destinations of commutes are located in the particular district. Ratio represents the result of JHR.

Moreover, we also counted the number of least (travel time < 10min) and highest (travel time > 90min) travel time of commuters in each district (as shown in Table 7). It can be seen that most commuters who travel more than 90 min come from Pukou, Luhe and Jiangning and commuters who travel less than 10 min mostly live in urban areas and Jiangning. This indicates that both short time commutes within Jiangning district and suburban-to-urban commutes from this district are frequent. This finding is consistent with Figure 9; its large number of working populations cannot enjoy the same level of public transit service due to the limited metro coverage compared with its vast area. So those live near public transport facilities enjoy a higher level of accessibility to work than those who not.

Table 7. The identified commuting trips in each district with least and greatest travel time.

Location	Name	Number of Trips (Travel Time < 10 Min)	Number of Trips (Travel Time > 90 min)
Urban	Xuanwu	1,290	21
	Qinhuai	1,580	11
	Gulou	1330	19
	Jianye	1170	29
Suburban	Yuhuatai	995	10
	Pukou	690	248
	Qixia	710	96
Exurban	Jiangning	1,410	156
	Luhe	90	265

In addition to the analysis at district-level, we also investigate the jobs–housing balance at a more micro level, so this study extends the analysis to the situation within a particular district. As shown in Figure 10a, the JHR of central urban is far more than other urban areas. This is because the Xinjiekou business area and Zhujianglu business area are all located in downtown, which attracts a large number of commuters to work there. At the same time, the JHR of some urban stations near the boundary between urban areas and suburban areas is less than 1, especially those in Xuanwu district. One possible reason is that those stations are near Zhongshan scenic area where the productive activity is not allowed. This leads to a relative lack of jobs. Furthermore, those commuters live in the urban fringe usually choose to work in the central urban areas, which results in a low value of JHR of urban stations near the boundary between urban areas and suburban areas. Concerning the suburban areas, most stations show the same situation as the whole districts. A low JHR of the terminal of metro line 2 located in Yuhuatai district (shown in Figure 10b) suggests that most nearby residents commute to other districts for work. This is because this station is close to one urban district (Jianye), workers who work in urban areas may choose to live in the place near this station in consideration of lower housing price. Another interesting finding is that the JHR of stations near the university is more than 1 in Jiangning district (as shown in Figure 10c). Since these are universities' new campus, the surrounding residential development and construction are not well established. Most relevant workers may choose to live in other districts with mature living service facilities.

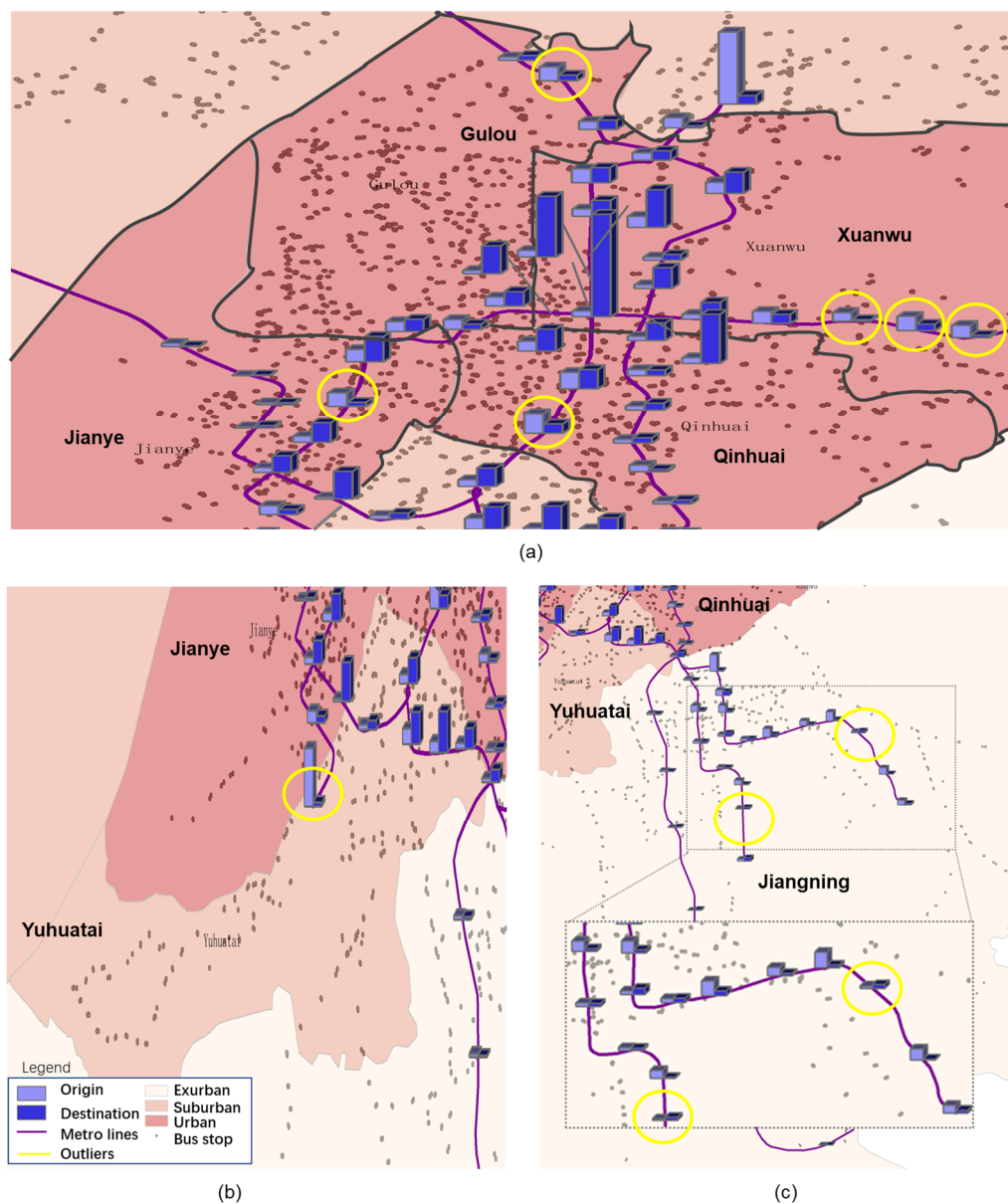


Figure 10. (a) The situation of jobs–housing balance around each station on urban areas; (b) The situation of jobs–housing balance around each station on suburban areas; (c) The situation of jobs–housing balance around each station on exurban area. Note: The Origin means the number of commuters leave from this metro station, the Destination means the number of commuters reach this metro station. The height of a bar chart means the number of trips.

Therefore, we can infer that industrial activities of Nanjing are mostly concentrated in urban areas and residents are transferring from urban areas to suburban and exurban areas with the process of suburbanization of residence (the proportion of Pukou, Qixia and Jiangning in the working population of the whole city reaches 53.981%). As a result, the over-concentrations of industrial activities in urban areas besides the inadequate industrial support and feeble centralize capability of suburban and exurban areas lead to the spatial mismatch between working places and residential locations.

6. Conclusions

This paper focuses the work commuting behavior in public transit system and explores the distribution of the commuters' travel time by metro and bus and the jobs-housing balance based on the smart card data of Nanjing (NSC). There are two main contributions in this study. First, the trip chain

based on an individual-level smart card data is used to identify commutes which improve the accuracy of analysis results. Second, Gini coefficients are used to show the distribution of commuting time then jobs-housing ratio (JHR) is calculated to reveal the matching degree between jobs and residential places in each district. These findings will be conducive to better planning of public transport facilities and secure housing for urban planners and policymakers.

A Lorenz curve approach is presented to compare the distribution of commuting time in each district. The results show that the Gini coefficient is 0.251 in urban areas and 0.262 in non-urban areas. According to the practical norm, both coefficients show that the proportion of medium-range commutes by public transit in all commutes is bigger in Nanjing. The gap of each non-urban district in commuting time is larger than urban districts; the average commuting time is longer in on-urban districts. A more significant Gini coefficient and a longer average commuting time suggest that more commuters in suburban areas experiencing long-distance commutes compared with commuters from urban areas. This result, at some degree, reflects the spatial mismatch between jobs and residential places exist in Nanjing. Based on Cervero's (1989) research, this study calculates the jobs-housing ratio (JHR). The result shows that the jobs of Xuanwu district are far more than the working population of this district, whereas the jobs and working population in other urban districts are relatively matched. The value of JHR is less than 0.8 in all suburban districts but Yuhuatai, that is to say, jobs of these districts are in short supply compared with their working population.

The jobs-housing mismatch reflects the urban spatial inequity from the perspective of jobs-housing relationship in space. The results of this study show that the home-work separation also exists in China and planners and policymakers should give more attention to this urban spatial inequity. As this inequity may restrict socially disadvantaged groups' ability in commutes, migration and information seeking, then becoming structural barriers that affect their choice in housing and working places [19,28]. In light of these findings, advice for planners and policymakers are further proposed. A rational planning of public transport facilities to meet more commuters' need in reducing commuting time. The construction of security housing should consider the distribution of jobs in order to alleviate the jobs-housing mismatch of medium or low-income stratum. All these strategies will contribute to help socially disadvantaged groups get more development space and chance. However, this study is based on a case study of Nanjing, an analysis of the mechanism of spatial mismatch on a larger scale is needed in further researches. Institutional and policy factors that are affecting the ability of socially vulnerable populations in adapting to the jobs-housing separation and spatial restructuring of cities should be introduced into the analytical framework to achieve a better understanding of the spatial inequity of China in the amid the transformation.

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