ACCESSIBILITY AND SOCIO-SPATIAL INEQUALITIES BETWEEN LOCALS AND MIGRANTS IN XIAMEN CITY, CHINA

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Accessibility and socio-spatial inequalities between locals and migrants in Xiamen city, China

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Contents

1. Introduction

Before 1978, China had a centrally planned system that encouraged rapid industrialization while maintaining a relatively low dependence on foreign economic investment (Crane *et al.*, 2018). The economic reform that created the special economic zones (SEZs) in the early eighties of the previous century was the starting point for the massive urbanization in China. SEZs refer to areas that employ special economic policies, flexible economic measures, and special economic management systems, aiming to stimulate economic growth by attracting foreign investment (Crane et al., 2018). The original four zones—Shenzhen, Zhuhai, Shantou, and Xiamen— were located in coastal areas close to Hong Kong, Macao, and Taiwan. During that period, Hong Kong, Macao, and Taiwan began to upgrade their industrial structures and transfer their labor-intensive manufacturing industries (Zeng, 2012). As a result, these special economic zones have undertaken many transferred industries and attracted a large amount of labor. Cities expanded with the development of huge industrial sites, and millions of rural migrants moved to the cities to work in the manufacturing industries. Xiamen was one of these SEZs that used foreign direct investments from Taiwan to drive the city's expansion. The three Taiwanese investment zones authorized by The State Council promoted the transformation of Xiamen from an "island city" in the 1980s to an "island–gulf city" in the 1990s (Cao & Liu, 2007). It was during this period that things began to change. In 1991, the Xiamen Bridge—known as China's first sea-crossing bridge—was opened, connecting Xiamen Island to its mainland areas. The continued construction of other cross-sea bridges and tunnels has strengthened the connection between Xiamen Island and the mainland areas. The manufacturing industries moved to its mainland area as industrial sites on the island were taken over by the rapidly expanding service sectors. Increasing spatial mismatch and cross-district commuting occurred as the result of the relocation of industrial areas towards mainland locations and the stay of quite some residents on the island.

Equally important was the reform of the housing system towards commodified housing that changed the spatial distribution of housing opportunities. The disintegration of the traditional *danwei* system made the housing and the basic facilities no longer provided in the vicinity of the industries, resulting in reduced access to employment and services. The increased travel distance caused by reduced accessibility has stimulated the change of travel modes from non-motorized mode to motorized mode. The increasing use of motorized mode, in turn, expanded the activity space of residents from the original spatial pattern where all activities took place within the *danwei* to the entire urban space. It is generally accepted that access to jobs and services (potential accessibility) and individual preferences and restrictions determine individuals' residential choice behavior and travel behavior (actual accessibility). The spatial pattern, economy, and society that have changed in the past 30 years have undoubtedly changed urban accessibility, and this changing accessibility is the topic of this thesis.

1.1 Changing accessibility in Chinese cities

Before the housing reforms in 1998, the so-called *danwei* system was China's dominant housing system. *Danwei* refers to institutions that provide various welfare-oriented facilities for urban residents (Chai, 1996). These entail besides housing and working also amenities and welfare facilities, although variations existed in the diversity of facilities offered. It was ubiquitously embedded into urban space, covering factories, shops, schools, hospitals, research institutions and cultural groups, and other enterprises and institutions (Lu, 1989). Most of these *danwei* built walls and gates to ensure the privacy of *danwei* workers and their families with enclosure space, gradually forming a sense of belonging (Bjorklund, 1986; Bray, 2005; Chai *et al.*, 2007). Life in the *danwei* system was convenient, encompassing employees' economic, political and social life (Li and Kleiner, 2001). All aspects of people's lives could be realized in *the danwei* compound. *Danwei* could be considered as a mini-society or self-organizing 'cell' embedded into a larger space, forming an urban mosaic with *danwei*-based distinctive zones (Wang and Chai, 2009). In the suburbs, large-scale *danwei* engaged in different industrial activities, integrating social life and political control, and appeared as independent small towns (Bjorklund, 1986; Bray, 2005). In the inner city, small-scale *danwei* could not afford their constellation of facilities but shared the living and housing facilities, and along the main street, poor quality single-story housing mixed with modern state-owned shops and offices. And in between, there was a ring of public institutions and their related housing (Wang and Murie, 1999). Under the *danwei* system, the commuting distance was relatively short since job-housing was highly balanced. According to Xu (2011), the average commuting distance within the *danwei* system was shorter than 3 km.

After the housing reform of 1998, the *danwei* system was no longer the provider of housing (Ta *et al.*, 2017), and the disintegration of the *danwei* system changed the spatial organization at the community level. On the one hand, housing reform has changed the housing system from a welfare-oriented public housing system to a mixed housing system of commercial housing, government-subsidized affordable housing (Zhang, 2009; Wang et al., 2011). With the rapid development of the housing market, the construction industry gradually became the pillar industry of the national economy. As buyers or renters began to seek housing within an open market, the spatial constraints for residential living derived from the *danwei* system have been relieved. The disintegration of the *danwei* system separated the economic activities from the daily activities of individuals and families, leading to the separation of workplace and residence (Chai *et al.*, 2011). On the other hand, community service facilities have changed from internal to external, from the original self-sufficient mode to the social sharing mode, and gradually integrated into the urban service-level network system (Zhang *et al.*, 2009). In the past, *danwei* was like a "city within a city" (Ma and Wu, 2005), where employees could meet all the needs of daily life. When these limits fell apart, residents were gradually attracted by the external urban service facilities, searching for services in a larger range of urban space to improve the quality of life (Zhang *et al.*, 2009). As a result, the accessibility of higher-level public services has become increasingly important.

Concurrently, the reform of the urban household registration system (*hukou*) changed the position of *danwei* at the city level. This *hukou* system originally tied Chinese citizens to their place of residence and restricted the population flows between *danwei*, and further limited the inter-city population flows (Chai, 1996; Chai *et al.*, 2011). Since 1984, when the State Council issued the "Notice on the Resettlement of Farmers in Market Towns", China has implemented a series of household registration system reforms that have eased restrictions on rural-urban migration (Liu *et al.*, 2018). The reform of the *hukou* system, coupled with the reform of the economic system, prompted a massive influx of migrants. Different from the local residents who began to buy relatively “affordable” housing directly after the housing reform, most of the rural migrants were not legally entitled to the affordable housing system and besides couldn’t afford excessive-priced housing (Fan, 2010). As a result, they did seek housing mainly through the private-owned rental market, especially informal housing in the so-called “villages in cities” (ViCs) or “urban villages” (Gu and Shen, 2003; Lin *et al.*, 2014, 2017; Liu *et al.*, 2017). According to Zhu *et al.*, (2017), these ViCs in general provide relatively good job accessibility so that migrants living over there commute shorter distances than migrant workers living in other types of urban settlement.

Another development at the city level that changed the urban spatial structure for the last two decennia concerns industrialization, suburbanization, and the development of motorized transportation. Since the 2000s, China has gradually become the world factory, and a great deal of large-scale industrial parks have been built in suburban areas. As illustrated by the bid rent theory (Alonso, 1964), the old manufacturing industries in the inner city could no longer afford the high land prices over there. As a result, the original manufacturing jobs situated in inner-city locations moved to the suburbs and were substituted by high-level jobs such as finance and business services. These locational changes in employment opportunities were not accompanied immediately by a change in transportation possibilities. The completion of the cross-sea bridge and tunnel since 1991 has greatly enhanced the connectivity between Xiamen Island and its mainland areas. According to the "2019 Xiamen Transportation Development Report", as of the end of 2019, the average daily traffic to and from Xiamen Island reached 538,600, an increase of 2.8% over the previous year. Equally important is the change in travel mode. In 1988, non-motorized mode, including walking and cycling, accounted for 84.9% of all trips, followed by buses (10.3%), and private cars accounted for 0%. Since then, the proportion of non-motorized modes was declining, and the proportion of public transportation has continued to rise. The proportion of bus trips increased from 27.5% in 2003 to 32.4% in 2009 and then dropped to 25.7% in 2015.

All these developments did influence individuals' activity space. As the original *danwei* system guaranteed close job-housing proximity and service-housing proximity, daily travel time in the *danwei* system was much shorter than in the existing urban system (Yao and Wang, 2018). For instance, commuting distance in Guangzhou has more than doubled between 1984 and 1998, when it increased from 2.54 km to 5.41 km (Deng *et al.*, 2000). However, despite the magnitude of changes in land use, transportation, and demographics, still there is a lack of insight into the causes and consequences of all this for the degrees and patterns of accessibility in Chinese cities. There has been a rising issue of inequality during the rapid economic growth accompanied by new urban poverty (Wu, 2004). It remains unknown whether changing accessibility further marginalizes weaker socioeconomic groups through processes such as residential segregation and spatial mismatch. As one of the original four SEZs, Xiamen realized marketization in the early stage and evolved a spatial pattern similar to that of Western countries to a certain extent. Simultaneously, China's unique system has evolved a spatial pattern that is somewhat different from that of Western countries. By taking Xiamen city as an example, this dissertation contributes to a better explanation of the causes and consequences of these contextual changes as well as the recent interactions between land use, transportation, and individuals in China.

1.2 Components and types of accessibility

Accessibility is a concept applied in a wide range of studies such as transport planning, urban and regional planning, and human geography, for business location selections, travel demand forecasting, population distribution studies, and public facility supply (Allen *et al.*, 1993; Pooler, 1995; Neutens, 2015; Wang and Chen, 2015). Accessibility is defined in several ways, including “the potential of opportunities for interaction” (Hansen, 1959), “the ease of travel to opportunities” (Nassir *et al.*, 2016), “the ease with which activity locations or urban opportunities can be reached from a particular location or by the individuals at that location” (Kwan and Weber, 2008). Given the fact that in this study accessibility is connected to structural changes in China in land use, transportation, and demographics, all those components are of relevance to include in the accessibility measures. Consequently, in this study accessibility will be defined as “the extent to which land-use and the transport systems enable individuals to reach activities or destinations by means of a (combination of) transit mode(s)” (Geurs and van Wee, 2004). This definition contains four interrelated components: the land-use component, the transportation component, the individual component, and the temporal component. These four components will be discussed over here, in the context of China.

- **Land-use component**

The land-use component describes the location-based information, consisting of (a) supply of opportunities at each destination (e.g. shops, health, social and recreational facilities, jobs, etc.), and the demand for these opportunities at origin locations (e.g. population) (Langford *et al.*, 2008). After the disintegration of the *danwei* system, the spatial relationships between different land uses have changed. On the one hand, after the limits of *danwei* walls fell apart, residents began to seek public services into a larger range of urban space (Zhang *et al.*, 2009). On the other hand, the traditional proximity of housing and working has gradually disappeared, and commuting distance has gradually increased. Meanwhile, along with the growing industrialization and urbanization, the land-use component changed substantially. As land prices in the central areas sky-rocketed, old manufacturing industries in the inner cities could no longer afford the high land prices and thus were gradually substituted by high-level jobs such as finance and business services. Furthermore, a great number of large-scale industrial parks have been built in the suburbs. Another land-use change worth considering is the formation of urban villages, which is the result of rapid urban expansion that has swallowed surrounding villages in the suburbs or outskirts. These villages have become "villages in the citys" (ViCs) or "urban villages", which provide housing for both local villagers and in particular rural migrants who are excluded from the official urban housing market due to their non-local *hukou* (Lin *et al.*, 2011). Given that these urban villages are typical Chinese phenomena, they should be considered as a land-use component when analyzing accessibility.

- **Transportation component**

The transportation component reflects the transport system, consisting of the supply of infrastructure, including its location and characteristics, as well as travel distance, travel time, and travel cost by a certain mode of transportation (Geurs and van Wee, 2004). After the disintegration of the *danwei* system, the dominance of non-motorized mode has been replaced by motorized mode. In Xiamen, the total percentage of non-motorized trips, such as walking and cycling decreased from 84.9% in 1988 to 41.6% in 2015. This is due to the continuous development of motorized vehicles and the increased travel distance caused by the separation of employment and residence. In terms of motorized mode, in China, public transportation rather than private car is of main importance. In the United States, about 90% of workers drive to work (Tilahun and Fan, 2014), and even low-income groups buy cars in order to benefit from increased job accessibility and to end their public transit-dependency (Sanchez *et al.*, 2004). In contrast, the development of private car motorization in China has only started in the last two decades. In Xiamen, the proportion of private car trips in modal split has risen from 4.1% in 2003 to 17.8% in 2015 (Xiamen urban planning and design research institute, 2015). In the past, the demand for motor vehicle travel was borne by public transportation, but with the development of private cars, the proportion of public transportation has slightly decreased. Specifically, the proportion of public transportation in modal split has risen from 10.3% in 1988 to 32.4% in 2009, then dropped to 25.7% in 2015 (Xiamen urban planning and design research institute, 2015). Therefore, the analysis of accessibility should consider the reasons, consequences, and their relationships with other components for choosing different travel modes.

- **Individual component**

The individual component describes the demands (related to age, education level, *hukou* status, occupation, etc.) and abilities (related to the availability of travel modes)

(Geurs and van Wee, 2004). In terms of the individual component, both job accessibility and public service accessibility in the Chinese context are different from those in the western context. For instance, in the Chinese context, the very specific *hukou* system has led to a degree of residential segregation and in inequity in social service accessibility. This *hukou* citizenship plays an important role in the accessibility of jobs, social welfare, and public welfare in a city (Lin *et al.*, 2011). For example, migrants with a rural *hukou* are ineligible for jobs in government and state-owned organizations and are excluded from public housing, public schools, and public healthcare in the city (Li and Liu, 2017). The imparity between holders of a local *hukou* and a rural *hukou* like migrants has caused huge differences in spatial behavior. For instance, low-income local groups can apply for public housing, which is often located in places with lower job accessibility (Zhou *et al.*, 2013). In contrast, low-income migrants, who are excluded from the public housing system, often rent private housing in urban villages, which are often located near industrial sites. As a consequence, for calculating the degree of accessibility within the Chinese context, individual components like *hukou* status have to be taken into account explicitly.

- **Temporal component**

The temporal component reflects the temporal opportunities and constraints for both the supply side (e.g. opening hours of shops and services) and the demand side (availability of time for activities) (Delafontaine *et al.*, 2011; Neutens *et al.*, 2012). Although in this study these temporal opportunities and constraints for the supply or demand side do not be taken into consideration due to data limitations, the temporal component of transportation is taken into account. Due to the inconsistency of road congestion at different times, the travel time of the same origin and destination at different times can be different, which affects its accessibility. This will be incorporated in the measurements with the help of a web-based accessibility instrument, which employs Gaode Maps application programming interface (Gaode API) to estimate accessibility by walking, public transportation, and private cars in real-time (Geurs *et al.*, 2015).

These four components do not exist in isolation but interact with each other. Therein, the land-use component is an important factor determining other components. For instance, the increasing distance between the supply and the demand of opportunities has changed the trend of travel mode from a foremost non-motorized mode to a growing motorized mode. Thus, to measure the actual degree of accessibility different modes of transportation (e.g., including motorized) and combinations of these (e.g., walking and public transportation) should be taken into account.

The individual component interacts with all other components. Individual preferences or limitations influence the locational choice (land use components) and mode of transportation (transportation component). For example, due to their lack of urban citizenship (*hukou*) and financial means, most rural migrants just have limited access to owner-occupied commercial housing, government-subsidized affordable housing, and government-subsidized rented housing in the city. As a consequence, most of these migrants rent villager's homes in ViCs, which often are closely situated near the main industrial working places. This is in contrast to the locations of homes of quite some locals with a local urban *hukou* who possess access to affordable housing and even can afford to buy themselves a home in the city, which is however not per definition closely located to main employment centers. These differences in locational choices of distinctive socioeconomic groups (for instance, locals versus migrants; blue-collar versus white-collar) will further influence their degree of accessibility and the resulting travel behavior. These differences in socioeconomic and institutional status and their distinctive influence on travel behavior have still not thoroughly been researched within the Chinese context.

In Geurs and van Wee (2004)'s explanation of the relationship between accessibility components, the relationship between the land-use component and transportation component is one-way, and land use determines transportation demand. Unlike their interpretation, the accessibility in this study is a concept that changes over time. In this sense, the transportation component also has an impact on the land-use component. The development of transportation infrastructure and means of transportation expands individuals' activity space and promotes the separation between different functions of the city, such as housing, work, and public services.

In this dissertation, the land-use component and the transportation component are considered the starting points to measure the degree of accessibility, while the individual component is considered the cause for divergence in travel behavior between distinctive groups. Accordingly, we can differentiate between "potential" indicators which highlight the spatial relationship between located activities, and "actual" indicators which emphasize individuals' travel behavior. On the one hand, accessibility can refer to the potential of opportunities for interaction rather than actual trip making (Hansen, 1959). This complies with Hansens' (1959) definition of accessibility as "a measurement of the spatial distribution of activities about a point, adjusted for the ability and the desire of people or firms to overcome spatial separation". On the other hand, accessibility can be regarded as related to actual behavior (Dalvi, 1978), such as accessibility to services and participation in activities (Morris et al. 1979), as well as travel time and distance (Niedzielski and Eric Boschmann, 2014). In this regard, the underlying correlations between actual travel time/distance and micro/macro-level factors have to be quantified. Therefore, in this study focus will be put explicitly on the relationship between people's distinctive socioeconomic and institutional status and their degree of accessibility of jobs and services.

1.3 Research objectives and questions

In the context of China's macroeconomic transformation and its accessibility-related consequences, it is crucial to understand how the macro-level land-use system and the transportation system interact with micro-level socioeconomic factors to determine potential and actual accessibility. There has been a rising issue of inequality during the rapid economic growth accompanied by new urban poverty (Wu, 2004). It remains unknown whether housing and economic reform further marginalize weaker socioeconomic groups through processes such as urban segregation and institutional discrimination. The overall aim is to understand the extent to which the geographical distribution of housing, jobs and services, and the transportation system affect the accessibility to jobs and amenities of different socioeconomic groups in Xiamen, China.

To achieve this research goal, a conceptual model has been established (Figure 1.1). Urban systems are complex dynamic systems that are developed by the interaction between macro- and micro-level factors. The land use and transportation components shape the static opportunity structure at the macro level, while the individual components generate the actual trips between different active nodes through the transportation system. Accordingly, actual accessibility is determined by the macro-level opportunity structure and micro-level individual components. In other words, residential location, employment/amenity location, transportation connecting the two locations, and socioeconomic and demographic factors determine the choice set for housing and commuting behavior. On the one hand, surrounding land use and transportation influence housing prices and rents. On the other hand, housing prices and individual's preferences and limitations influence location choice for housing. As home is the place where activities originate, its surrounding land use components and transportation components determine the degree of potential accessibility at the macro level. The individual component, together with land-use components and transportation components influences the degree of accessibility and the resulting travel behavior.

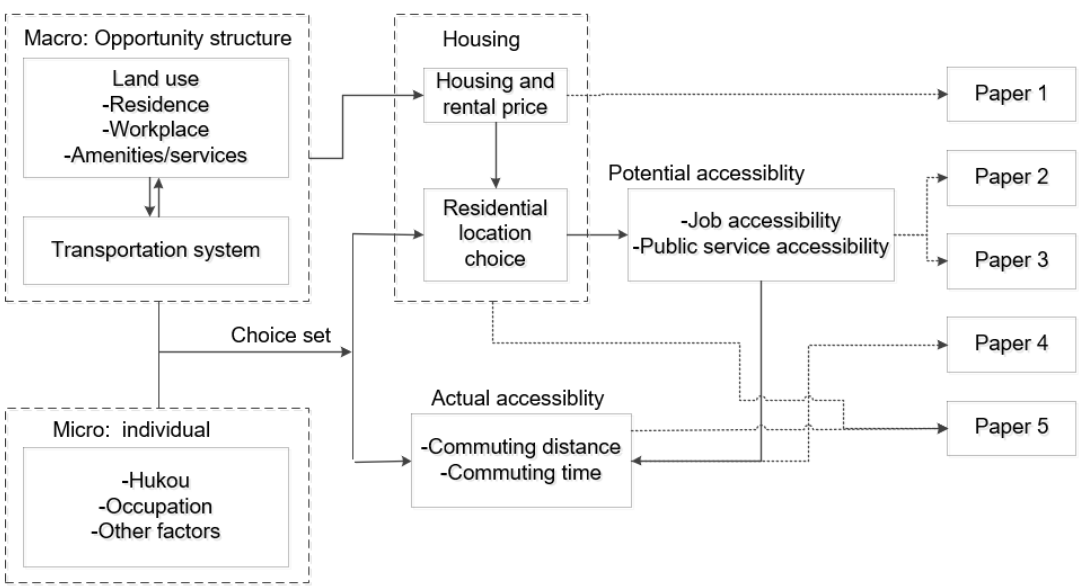

Figure 1.1 Conceptual model

Golledge (1997) argued that one's home is the place that generates the greatest number of trips and is the place where activities originate. When competing for housing, different socioeconomic groups have different selection criteria and capabilities. For instance, looking at a study on Nanjing by Hu *et al.* (2014) the lower-middle class cannot afford to rent or buy dwelling units in the central districts in Nanjing, which will affect their accessibility to jobs and amenities and in that their travel behavior (Hu *et al.*, 2014). It implies that housing locations with different housing prices attract distinctive socioeconomic groups. Thus, we will start by examining the market price determinants of owner-occupied housing and rental housing (Chapter 2). Next, at the macro level, potential accessibility will be measured, including accessibility to jobs and public services (Chapter 3 and Chapter 4). Finally, at the micro level, actual accessibility will be measured, including commuting time and commuting distance (Chapter 5), and long-distance commuting behavior (Chapter 6).

1. To what extent do jobs, services, and transportation influence market prices in the rental and owner-occupied housing markets?

Due to differences in preferences and limitations, distinctive socioeconomic groups (blue-, pink-, and white-collar workers) seek their housing in distinctive housing markets. Blue-collar workers are those who work in labor-intensive jobs; Pink-collar workers refer to those engaged in service-oriented jobs; White-collar workers are those who perform professional jobs. Determinants of market prices in these distinctive housing markets may differ, for instance, due to differences in housing requirements between distinctive groups of homeowners and renters. To date, insight into the determinants of market prices in distinctive housing markets in China is restricted. By classifying the housing market into four submarkets—inner-district owner-occupied housing, outer-district owner-occupied housing, inner-district rental housing, and outer-district rental housing—Chapter 2 investigates the determinants of market prices for these distinctive housing submarkets in Xiamen with the help of a hedonic price model. Therein, we consider land-use variables (including the accessibility of jobs and amenities) and transportation variables (including the existing and the planned transportation system) as important impact factors for market prices in these distinctive housing markets.

2. To what extent does the accessibility of urban public facilities corresponds to the needs of distinctive socioeconomic groups of residents?

Accessibility of urban public facilities is essential for arriving at equality in sustainable urban development and high quality of life. However, most existing studies on the accessibility of public facilities just focus on one particular facility (Apparicio *et al.*, 2008; Grubesic and Durbin, 2017; Fasihi and Parizadi, 2020), which fails to reveal the internal or external effects of overall urban public facilities on residents. In order to formulate a more balanced facility allocation strategy, there is a need for an integrated measure of accessibility that includes different kinds of urban public facilities. To fill this gap, Chapter 3 analyses the overall accessibility of diverse types of public service facilities by different travel modes. Taking Xiamen city as a case study, it explores the degrees of horizontal and vertical equity by examining the accessibility of various basic public facilities, paying attention to different travel modes and travel times. The results can identify areas where access to basic public facilities is in need of substantial improvement. The methodology entails combining open data and travel survey data to analyze the accessibility of public facilities for different socioeconomic groups.

3. To what extent do distinctive socioeconomic groups differ in terms of the degree of spatial mismatch?

Compared to U.S. cities, Chinese cities are often presumed to be more resistant to spatial mismatch problems (Fan *et al.*, 2014), since most Chinese cities are characterized by high densities, well-developed public transportation systems, and lower levels of segregation (Kenworthy and Laube, 1999; Knaap and Zhao, 2009). However, these views may be biased and wrong in the present timeframe, for China has undergone tremendous changes in its urban spatial pattern over the past two decades. This research aims to provide a more accurate picture of job accessibility and spatial mismatch for distinctive socioeconomic groups. Therefore, chapter 4 explores differences and commonalities in job accessibility and spatial mismatch of distinctive socioeconomic groups by optimizing the dissimilarity index to identify spatial differences at the disaggregated level. With the utilization of open (big) data, we measure job accessibility for distinctive socioeconomic under different travel modes. On this basis, an enhanced dissimilarity index for distinctive socioeconomic groups is also calculated.

4. To what extent do distinctive socioeconomic groups differ in their actual commuting behavior?

Although there is a growing body of literature on the commuting pattern of migrants (Zhao and Howden-Chapman, 2010; Li and Zhang, 2011; Lau, 2013; P. Zhu *et al.*, 2017), up till now few studies have been conducted to understand the divergent commuting patterns of distinctive occupational worker types. For instance, job distribution, housing choice, and housing affordability is very divergent between blue-collar, pink-collar, and white-collar workers, in particular too when dividing these groups in local and migrant workers. Ignoring those differences will prevent us from understanding the differences between for instance local and migrant workers in commuting behavior. To fill these gaps, Chapter 5 examines the differences and commonalities in commuting behavior for distinctive socioeconomic groups, the underlying causes and the resulting consequences like emerging spatial mismatch. To better understand the similarities and differences in commuting patterns of these distinctive socioeconomic groups, we applied a linear regression model. Therein, use is made of the 2015 Xiamen household travel survey for determining the actual spatial mismatch of the distinctive socioeconomic groups.

5. To what extent is there a divergence in residential location choice and cross-district commuting among distinctive socioeconomic groups?

Commuting behavior is a result of the combined effect of land-use, individual and transportation componets. Although specific socioeconomic groups may be affected differently by the recent spatial and economic restructuring in Chinese cities, previous studies paid just little attention to this aspect. On the one hand, it is important to understand the extent to which the restructuring influences the residential locational choices of distinctive socioeconomic groups. On the other hand, it is worth exploring how distinctive socioeconomic factors affect long-distance commuting under the constraints of these location choices. With this in mind, Chapter 6 explores the determinants of residential choice and how residential choice in conjunction with socioeconomic factors influence cross-district commuting. To do so, a 2-step model is conducted which examines the determinants of residential choice in the first step, followed by exploring the determinants of the resulting long-distance commuting in the second step.

1.4 Study area: Xiamen, China

Xiamen, like Shenzhen, Zhuhai, and Shantou, is one of China's original four SEZs in China, covering an area of 1,699.39 square kilometers. Located in the coastal area close to Taiwan, Xiamen has received a large amount of Taiwanese investment in the past 30 years and has undertaken labor-intensive manufacturing transferred from Taiwan. With the development of large industrial zones, cities have expanded, and millions of rural immigrants have poured into cities. The built-up area has spread from the southwestern coastal area—the original Island—to all other districts, reaching 389.48 square kilometers in 2017. As one of the original four SEZs, Xiamen opened to the outside world in the early period and evolved a spatial pattern similar to that of Western countries to some extent. In Xiamen, only about 1 percent of households live in *danwei* housing, and many have shed the walls of the traditional *danwei* system (Xiamen urban planning and design research institute, 2015). This makes Xiamen a good case for studying the spatial structure of Chinese cities since marketization.

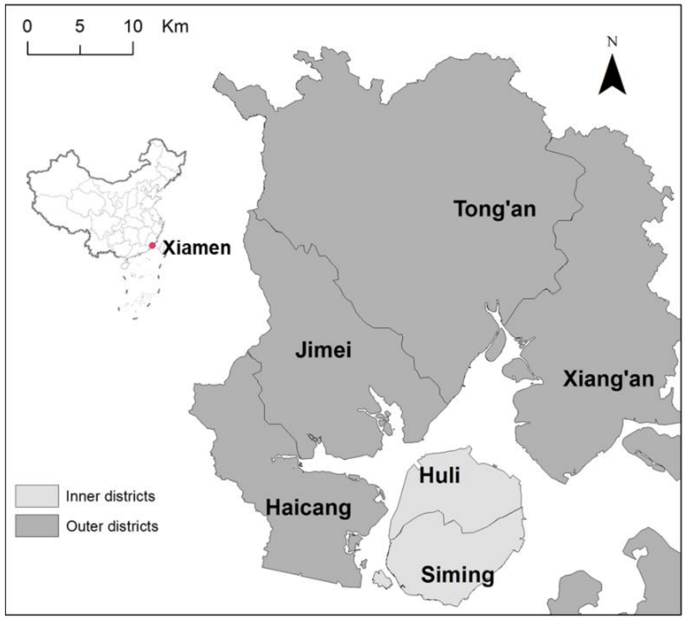

Figure 1.2 Location and administrative division of Xiamen

In 1980, Xiamen SEZ only referred to the area of 2.5 square kilometers of Huli, which was barren sand without grass. In 1984, the Xiamen SEZ expanded to the whole Xiamen Island (inner districts) with an area size of 131 square kilometers. In the late 1980s and early 1990s, the State Council successively approved Taiwanese investment zones in Haicang, Jimei, and Xinglin. Subsequently, other Industrial Development Zones were successively approved by the State Council. In 2002, Xiamen promoted relocation of the Island's industrial enterprises, accelerating the construction of industrial zones outside Xiamen Island (outer districts). In 2014, the proportion of industrial output value in outer districts accounted for two-thirds of the city total (Xiamen Municipal Statistical Bureau, 2015).

After housing reforms, the housing market in the inner districts developed rapidly. In December 2004, transacted new housings in the inner districts and outer districts were 1663 and 580, respectively (Xiamen Municipal Bureau of Land Resources and Real Estate Management and Xiamen Municipal Statistical Bureau, 2017). Two years later, transacted new housings in the outer districts exceeded the number in the inner districts, as the new housing market in inner districts was saturated while the market in outer districts continued to develop. From 2013 onwards, the volume of new housing transactions in the inner and outer districts has continued to decline. Instead, the second-hand housing market developed rapidly. In 2017, second-hand housing transactions in the inner districts and outer districts were 15,626 and 12,434, respectively (Xiamen Municipal Bureau of Land Resources and Real Estate Management *et al.*, 2017). Besides the new housing market and second-hand housing market, the rental housing market is also of importance in Xiamen. In that, there are significant differences in housing decisions between local and non-local populations. According to Xiamen household travel survey, in 2015, 91.88% of the local population lived in owner-occupied housing, while 80.71% of the migrant population lived in rental housing.

With the urban expansion and the increase in distance between various functions of the city, the dominant position of non-motorized mode in total trips has been gradually declining, especially cycling trips, which dropped from 49.1% in 1988 to 11.3% in 2015 (Xiamen urban planning and design research institute, 2015). The modal split of walking has not changed much, remaining in the range of 30-40% since 1988. In terms of motorized mode, despite a sustained growth in car modal share, the share of public transportation (25.7%) is still greater than that of private cars (17.8%) in 2015. The public transportation system consists of bus, Bus Rapid Transit (BRT), and metro system. Xiamen's Bus Rapid Transit (BRT) began to operate in 2008, which is considered China's first elevated BRT network. The development of the metro system is of later date than the BRT, which began its operation on 31 December 2017. During the time frame covered by this study, the metro has not been operating.

1.5 Thesis outline, data, and methodology

The thesis consists of seven chapters. Chapters 2 to 6 are based on papers that have been (re-)submitted to and/or published in international peer-reviewed journals. Therefore, there are some overlaps in descriptions on data and backgrounds of study areas.

Chapter 2 examines the determinants of market prices for housing submarkets: inner district owner-occupied housing market, outer district owner-occupied housing market, inner district rental housing market, and outer district rental housing market. Particularly, we examine how transportation variables and land-use variables influence market prices for distinctive housing markets. Housing data were collected from a widely used housing sales and rental service platform in October 2018 (https://xm.lianjia.com/). The data were crawled in python, and in total, data on 2,735 housing unit sales and 1,378 housing unit rentals were selected. A hedonic model was applied to analyze differentiation in the determinants of housing prices between the four submarkets. In addition to ordinary least squares (OLS), spatial error model (SEM) and spatial lag model (SLM) were adopted to eliminate spatial autocorrelation.

Chapter 3 explores the degrees of horizontal and vertical equity by examining the accessibility of diverse types of public service facilities, paying attention to different travel modes and travel times. Points of Interest (POI) data—including hospital, shopping amenities, cultural facilities, sports amenities, recreational amenities, parks, and schools—and travel time matrix data were collected from Gaode API (https://ditu.amap.com). We developed an enhanced two-step floating catchment (2SFCA) that integrated the actual travel behavior into predefined thresholds, weights, and travel impedance factors. We corresponded to different levels of facilities with different travel modes: community-level public facilities corresponded to non-motorized modes, and district-level public facilities corresponded to motorized modes. An enhanced two-step floating catchment area (2SFCA) was developed, which incorporated actual travel behavior into predefined thresholds, weights, and travel impedance factors. Spatial inequalities were manifested by accessibility measures. Vertical equity was assessed by examining the integrated accessibility in terms of different groups. To integrate sociodemographic variables and mobility needs and ability into a small number of factors, a factor analysis method was used.

Chapter 4 focuses on the job accessibility for different socioeconomic groups, including blue-, pink-, and white-collar locals and migrants, and compares the spatial mismatch for these groups. Firm data—which includes employment information—were obtained from the Xiamen Municipal Bureau of Commerce, including 65,891 firm records and 2,026,217 jobs in total. Job accessibility was measured by walking and public transportation for distinctive groups of blue-collar, pink-collar, and white-collar workers, differentiated in locals and migrants. The dissimilarity index was optimized at the disaggregated level so that it could indicate the spatial disparities of local and migrant workers.

Chapter 5 examines the differences and commonalities in commuting behavior for distinctive groups of blue-collar, pink-collar, and white-collar workers, differentiated in locals and migrants - the underlying causes and the resulting consequences like an emerging spatial mismatch. Travel data were obtained from the Xiamen household travel survey in 2015 conducted by the Xiamen urban planning and design research institute. A total of 40,201 households were selected and 120,603 individual travel survey forms were issued in this survey, which covers 3% of the total population in Xiamen. We used an ordinary least squares (OLS) regression model to examine the impact of *hukou* and occupation on commuting distance and commuting time. Interaction between *hukou* and occupation was incorporated into our model in order to "moderate" the effect of the other.

Chapter 6 explores the determinants of residential choice, and how this residential choice and socioeconomic factors influence long-distance commuting. To do this, a 2-step model is conducted which examines the determinants of residential choice in the first step, followed by exploring the determinants of the resulting long-distance commuting in the second step. The basic idea behind these sample selection models is to model the prior selection into binary states (inner vs. outer districts) in the first step, and then model the outcome of travel behavior (cross-district commuting vs. intra-district commuting) as a conditional on that prior selection in the second step (Cao et al., 2009). Because of the binary dependent variable in the second step, we conducted a Heckman probit model, which enabled the estimation of binary-dependent outcome variables.

We finalize the thesis by Chapter 7 on conclusions and discussions, where we return to each of the research questions raised before and provide some further insights into the theoretical and policy implications of this research.

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2. The effects of jobs, amenities, and locations on housing submarkets in Xiamen City, China

ABSTRACT

Numerous studies have found that jobs, amenities, and location influence housing prices in urban areas. However, there is still a lack of in-depth understanding of the impacts of these factors on various housing submarkets within a city. With the case study of Xiamen, this paper investigates the impacts of jobs, amenities, and location on four housing submarkets, classified by owner-occupied and rental housing, in inner and outer districts. A hedonic model is applied to analyze differentiation in the determinants of housing prices between four submarkets. The results show that all submarkets are influenced by blue-collar jobs (which have negative effects) and seascape (which has a positive impact). Besides, differentiated after submarkets it shows that school districts, urban villages, and public transportation have a greater influence on owner-occupied markets than on rental markets. A heterogeneity exists between inner-district and outer-district markets. For instance, bus rapid transit (BRT) has a positive effect on house sale and rental prices in the outer-districts but not in the inner-districts. These differences are mainly caused by the disparities of spatial quality, economic development, and public facilities and amenities. The findings have profound implications for decision-making and planning practices.

Keywords: housing prices, submarkets, hedonic price model, accessibility; owner-occupied housing; rental housing

2.1 Introduction

There is a growing body of literature recognizing that the housing market consists of a series of submarkets. Definitions of housing submarkets may influence the reliability and accuracy of estimated housing prices (Biswas 2012; Jang and Kang 2015). Submarkets refer to “groups that are homogenous within and heterogeneous with respect to other groups” (Wu and Sharma, 2012, p.1). Housing submarkets are often defined in terms of geographical areas, relying on existing geographic boundaries, political territories, or spatial partitions based on socioeconomic or environmental characteristics (Alas 2020; Bourassa et al. 2003). Most of the existing studies have focused on the predictability power of submarket analysis, housing price diffusion patterns at different geographical levels, and the relationships between housing prices and economic fundamentals (Bangura and Lee 2020). However, the findings are mainly attuned to well-developed contexts, where submarkets have emerged and evolved for several decades. For instance, the majority of housing markets in U.S. metropolitan areas experienced an increase in segregation resulting in the formation of different housing submarkets between 1960 and 1970 (Schnare and Struyk 1976).

In China, a large number of houses have been constructed in the last 20 years to meet the demand of rapid population growth in cities (Ling and Hui 2013). The burgeoning market has some distinct features, such as the prevalence of new houses and a movement from welfare housing to houses in the private sector (ibid). Institutional factors that were inherited from the socialist planned economy and burgeoning market mechanisms have interacted to intensify housing differentiation and segregation (Wei et al. 2020). Chinese society has increasingly become more heterogeneous, reflecting in the formation of various socioeconomic groups and their different housing choices in diverse locations. For instance, most of the rural migrants, especially blue-collar workers who have engaged in labor-intensive jobs, live in the so-called "villages in the city" (ViCs) or urban villages near to commercial and industrial zones (Lin et al. 2014). Other socioeconomic groups such as pink-collar (who perform service-oriented jobs) and white-collar workers (who engage in professional jobs) also have their own preferences and limitations in housing location choices. These differences in housing location choices of distinctive socioeconomic groups could further influence their travel behavior and the degree of accessibility. In turn, the accessibility of jobs, amenities, and location will affect housing prices to varying degrees. From a comparative study between the inner city and outer suburbs, Li et al. (2019a) found that access to public transportation is less important in the inner city than in the outer suburbs.

Different socioeconomic groups not only have diverse housing location choices, but also distinctive housing ownership. According to the 2015 Xiamen household travel survey, 88% of citizens with local *hukou* are homeowners, while only 18% of migrants are homeowners. There are many differences between rental housing and owner-occupied housing in terms of flexibility and influential factors. As noted by Donner (2012), the inherent instability of rental housing can increase renters' flexibility in their residential mobility, especially for those having frequent changes of workplaces. Zheng *et al.* (2016) found that a high-quality school district has a price premium for owner-occupied housing but has no effect on rental housing in Beijing City. More research is required to understand the influence of different amenities and other factors on the submarkets of owner-occupied and rental housing.

There has been increasing interest in the influence of public facilities on housing prices in Chinese cities. Nevertheless, the existing research has not fully recognized the heterogeneity of the submarket caused by different socioeconomic groups, and the inconsistency of the influence of jobs, public services, and other factors in different submarkets. Therefore, this study expands the limited existing literature. It develops a conceptual framework for examining the influence of jobs, amenities, and public facilities on housing submarkets. A hedonic price model is applied to examine the relationship between urban amenities, jobs, traffic facilities, and house sale and rental prices. This research takes Xiamen City as a case study. Xiamen is a large city located in the southeastern coastal area of China, which has experienced rapid urbanization since the economic reform in the 1980s. The city has a heterogeneous population of approximately 4 million people, very different in socioeconomic and institutional (*hukou*) status. It is a good example to examine the role of housing submarkets in Chinese cities.

This article is structured as follows. In section 2, we review the determinants of house sale and rental prices and establish a conceptual framework on housing submarkets. In Section 3, we introduce the study area, methods, and variables of the hedonic price model. In Section 4, we present the findings of our empirical study in Xiamen. This is followed by our conclusion in Section 5.

2.2 Literature review

2.2.1 Determinants of house sale and rental prices

Hedonic price models establish a functional relationship between housing prices and several attributes that can be divided into three major classes: residential structures, locational attributes, and neighborhood qualities (Hu et al., 2019; Rosen, 1974). One approach to deal with housing submarkets is to compose separated hedonic price models for each submarket (Bourassa et al. 2003; Goodman 1981).

First, the structural attributes comprise building age, floor levels, and the number of rooms (Jang and Kang 2015; Saleem et al. 2018). In general, these factors have similar effects on different submarkets. A common finding is that house sale and rental prices decrease with building age (Hu et al. 2014; Wen et al. 2014). The number of bedrooms and living rooms has a positive effect on housing and rental prices (Choumert et al. 2014; Pride et al. 2018). In China, high floors often have higher prices due to their better views and less noise (Jiao and Liu 2010; Li et al. 2016). Whether an apartment is furnished or not also has a significant effect on its price (Tian 2006).

Second, there are several locational attributes. People are usually willing to pay more money for better access to amenities, therefore locational attributes influence housing prices (Basu and Thibodeau 1998). These urban amenities include cultural attractions, sports centers, shopping facilities, and hospitals (Huang et al., 2020; Jang and Kang, 2015; Tse and Love, 2000; Wen and Tao, 2015). Access to jobs also influences housing prices (Li et al. 2016), but overall job accessibility may fail to discriminate the differences. Moreover, different economic sectors can have diverse effects on housing prices (Ma, 2002). As noted by Hu et al. (2014), heavy industry has a negative effect on housing prices, while other economic sectors have a positive effect. As for the impact of different economic sectors on the rental submarket, it is still unclear. Furthermore, people are willing to pay more money for greater levels of accessibility to traffic facilities (Competencia 2008; Tian 2006). However, Li et al. (2019a, 2019b) argued that the influence of traffic facilities varies in different submarkets. They found that proximity to a metro station has greater effects on the suburban market than the inner-city market since public transportation is virtually ubiquitous in the inner city rather than in the suburbs.

Third, neighborhood variables play a pivotal role in influencing housing prices. Many studies have shown that school quality can have a positive effect on housing prices especially in Chinese cities (Agarwal et al. 2016; Haurin and Brasington 1996; Wen et al. 2015), but no effect on rents (Zheng et al. 2016), since the enrollment of the primary school is only bundled with homeownership in China. Previous research has also shown that attractive seascapes and landscapes, such as parks, green spaces, rivers, and lakes, have a positive effect on housing prices (Chou et al. 2015; Nilsson 2015; Yang et al. 2016). Lastly, evidence shows that housing prices can be lower in those neighborhoods close to the informal settlements of urban villages (Chen and Jim, 2010; Song and Zenou, 2012). So far, however, on the effects of different urban villages on the rental submarket not much is known.

Although a growing body of literature has studied the relationships between housing prices and several attributes, many existing studies have failed to identify the differences in determinants among housing submarkets. This study will bridge the gap by examining the differences between the determinants of house sale and rental prices in various submarkets in Xiamen City. For this, the housing market has been subdivided into housing submarkets that differentiate in terms of owner-occupied housing and rental housing located in inner and outer districts.

2.2.2 Conceptual framework

Understanding housing market variations within urban regions could be traced back to Alonso's theory of bid rents (Alonso, 1964). However, subsequent work showed that the structure of real-world cities is much more complex. Certain areas may trigger different social and physical development patterns in a historical period, which are then reflected in the subsequent characteristics of these areas through the process of "path dependence" (Bramley et al. 2008). The hedonic price model, which is the most commonly used statistical model of house price or rent changes, shows that house sale and rental prices depend foremost on their internal and external characteristics (Lisi 2019). Nevertheless, buyers may be willing to switch to other types of housing if they cannot get their first choice. This suggests that different parts of the market may operate semi-independently even within an urban area, resulting in housing submarkets (Bramley et al. 2008).

The specification of housing submarkets can be done in several ways, one of which is a spatial specification emphasizing a predefined geographic area (e.g., inner/outer city) along with people’s homogenous choice preferences (Gabriel and Wolch 1984; Xiao 2017). Most studies have focused on owner-occupied housing (e.g. Bangura and Lee, 2020; Keskin and Watkins, 2017), while some studies have combined owner-occupied and rental housing (Halket and Pignatti 2015; Jun and Namgung 2018). For instance, Halket and Pignatti (2015) defined a submarket as “all housing for rent or sale within a zip code with the same number of bedrooms." Moreover, the housing submarket could be divided based on the characteristics of housing structures, such as floor area and lot size (Halket and Pignatti 2015; Watkins 2001). Some scholars have divided submarkets by race (Palm 1978) or household income (Palm 1978; Schnare and Struyk 1976), which has been criticized by Watkins (2001) for their unsatisfactory results. A broader classification has been developed by Alkay (2008), who linked household income with geographical location. Alkay (2008) did chose old inner-city housing areas to represent middle-income groups, new block housing areas to represent high-income groups, and squatter settlements to represent low-income groups. The results show that there are significant price differences between the three submarkets. Another method is to classify submarkets by statistical analysis, such as factor analysis and cluster analysis. Although some scholars argue that submarkets generated by statistical analysis are better than an a priori classification, the improvement is not obvious (Bourassa et al. 1999).

In our analysis, we use a priori classification rather than a statistical analysis. Many scholars have provided evidence for the existence of submarkets (Bourassa et al. 1999). Similar to Alkay (2008), we link socioeconomic characteristics to a predefined geographic area and study the determinants of owner-occupied and rental markets separately (Figure 2.1). The main reason is that many studies have proven that the segmentation of the housing market is related to the behavior of people who adopt very different geographic strategies (Cox and Hurtubia 2020; Watkins 2001). For instance, there exists a considerable difference between locals and migrants in choosing within and between the owner-occupied and rental submarket. Due to institutional barriers like their non-local *hukou* and their low-income status, the majority of rural migrants within the city are not able to purchase commodity housing and as a consequence lives in private rental housing or dorms provided by employers (Liu et al., 2020). This is reflected in the figures—2015 Xiamen household travel survey—that shows that less than 20% of migrants are homeowners while more than 90% of local residents are homeowners. It reveals that the owner-occupied market is dominated by locals, while the rental market is dominated by migrants. Additionally, geographical factors are an important factor that affects submarket prices, and spatial preference and limitations exist between different socioeconomic groups. With the rapid industrialization and urbanization in China, new housing markets have emerged in the suburbs of many cities. Most new housing is developed on what used to be farmland, resulting in a lack of urban services for at least some time. Accordingly, a predefined geographic area along with people's homogenous choice preferences can be classified as inner and outer districts. According to the 2015 Xiamen household travel survey, more than 50% of pink-collar and white-collar locals lived in the inner districts with higher accessibility while only 30% of blue-collar locals lived there. This suggests that different socioeconomic groups have references or limitations in selecting specific submarkets, which will result in different degrees of accessibility due to varied geographical characteristics. Therefore, our model includes a number of key factors, including the mentioned three types of jobs, amenities (e.g. hospital, parks, shops, sports), transportation facilities (e.g. bus, metro), and neighborhood qualities (e.g. school district, urban villages, landscape). These factors can affect housing selling and renting prices in the inner and outer districts.

A considerable number of studies have proven that a separate evaluation of potential submarket models has a superior predictive power than overall market evaluation (Chen et al. 2009; Leishman 2009). Therefore, we evaluate the submarkets separately and examine how each determinant diversely affects them. The evaluation results in turn reveal the advantages and disadvantages of different groups regarding housing choices.

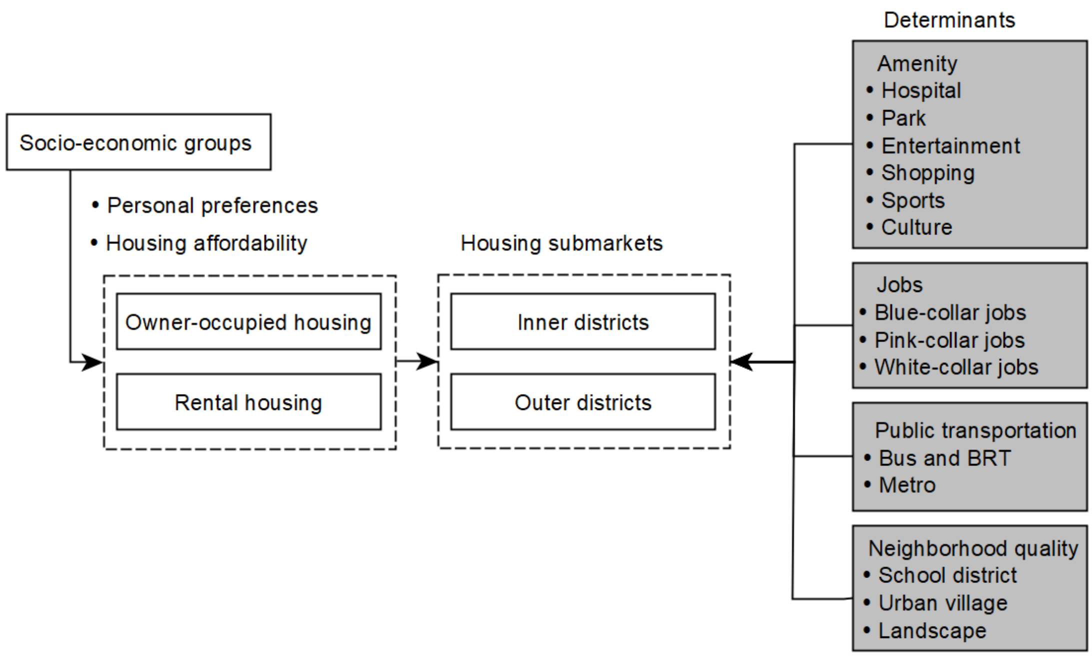

Figure 2.1 Conceptual framework for housing submarkets

2.3 Methodology

2.3.1 Study area and data

Xiamen City is located in the southeastern coastal area of China. The urbanized area of the city has spread from two inner districts (Siming and Huli) in Xiamen Island to Xiamen’s four mainland/outer districts, namely of Haicang, Jimei, Tong'an, and Xiang'an. In 2017, the permanent population of Xiamen reached 4 million, 50% of whom were migrants.

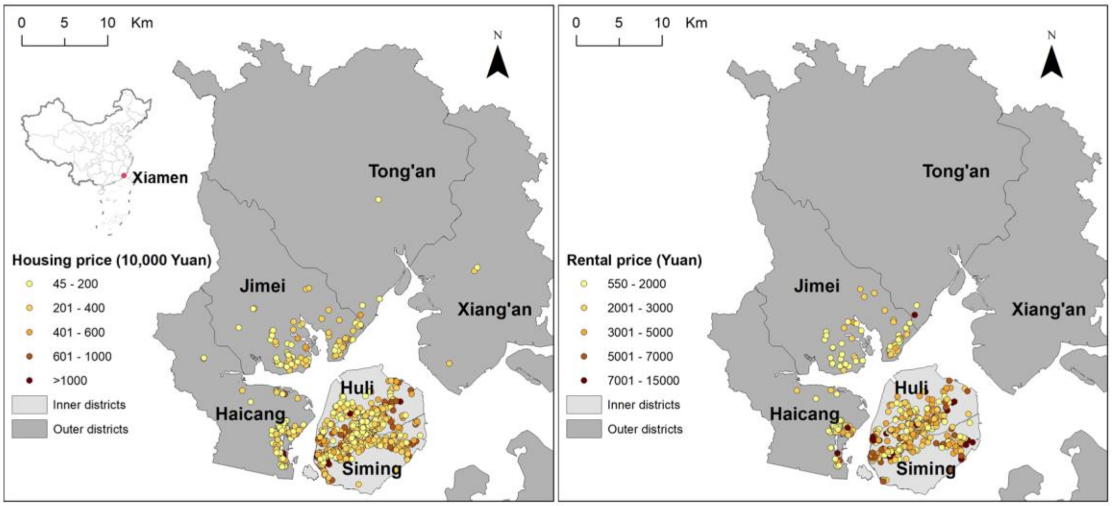

Figure 2.2 Distribution of house sale and rental prices in Xiamen

Multiple datasets were collected and used in this research. Housing transaction data were collected from a widely used housing sale and rental service platform in October 2018 (https://xm.lianjia.com/). In total, data on 2,735 housing unit sales and 1,378 housing unit rentals were selected (Figure 2.2). Another dataset was provided by the Xiamen Municipal Bureau of Commerce, including 65,891 company records and employment data of 2,026,217 jobs. Geographic information on amenities including culture, entertainment, exercise, hospitals, shopping, and parks—was obtained from an open data platform - Baidu API. In addition, high-quality school district data were collected from the "Xiamen Bianmin[1] Network" (http://m.xmbmw123.com/).

2.3.2 Methods

In line with previous studies, we applied a hedonic price model to examine the relationship between urban amenities, jobs, traffic facilities, and housing and rental prices. The hedonic price function (HPF) for our ordinary least squares (OLS) model can be formally expressed as:

$$\mathrm{LN(P)} = \alpha + \beta S + \gamma L + \eta N + \theta T + \varepsilon \qquad (1)$$

where $\mathrm{LN(P)}$ is the natural logarithm of the transaction price; S, L, N, and T represent structural (S), locational (L), neighborhood (N), and transaction time (T) variables; α, β, γ, η, and θ are the corresponding parameters; and ε is the random error term.

However, the traditional OLS model has a limitation, i.e. it neglects spatial autocorrelation. In order to test spatial autocorrelation, we calculated spatial weight. To build the spatial weights matrix, we created neighbours for each housing location

[1] This website provides some information services, such as household registration, enrollment, entrepreneurship, etc

beforehand (Bivand 2017). We built graph-based neighbours, choosing 4 nearest neighbours for each location to build the spatial matrix.

The Moran's I values of the four submarkets range from 0.150 to 0.283 at significant level, indicating the existence of spatial autocorrelation. To select the alternative models, we conducted Lagrange-multiplier (LM) test. The results show it is better to choose the spatial error model (SEM) for for inner- and outer-district owner-occupied housing and inner-district rental housing and the spatial lag model (SLM) for outer-district rental housing.

SEM model can be presented as:

$$\mathrm{LN(P)} = \beta S + \gamma L + \eta N + \theta T + \mu \text{ where } \mu = \delta W \mu + \varepsilon \tag{2}$$

where μ is a n×1 vector of error term; W is the standardized n×n weight matrix; δ is a spatial autoregressive parameter.

SLM model can be presented as:

$$\mathrm{LN(P)} = \alpha + \rho WP + \beta S + \gamma L + \eta N + \theta T + \varepsilon \tag{3}$$

Where WP represents the spatial lag of observations with n×n weight matrix W, and ρ is its corresponding parameter.

2.3.3 Variables

The description of variables is shown in Table 2.1. In this study, we adopted three main categories of independent variables: residential structure, locational attributes, and neighborhood quality. In line with previous studies (Li et al. 2019a; Wen et al. 2014), we selected interior (Degree in interior decorating), total floor area, number of bedrooms, number of living rooms, and the building’s age as our structural variables. As our data covers a period from 2016 to 2017, we added a time dummy variable to control temporal effects, which was adopted by many previous studies (Agarwal et al. 2016; Kang 2019).

Consistent with existing literature, we selected culture, sports, hospitals, shopping, and parks as our locational variables. In terms of job accessibility, we differentiated between different economic sectors. In line with Fan et al. (2014), we divided economic sectors into three levels: blue-collar jobs, pink-collar jobs, and white-collar jobs. Traffic facilities include bus stops, bus rapid transit (BRT), and metro. Xiamen's BRT system, which began operation in 2008, is considered to be China's first elevated BRT network. The first metro line began to be operated on 31 December 1, 2017. Since the selected housing price data is the data of 2016 and 2017, there are no operational lines during this data period.

Neighborhood variables like school quality (Agarwal et al. 2016; Wen et al. 2015) and attractive landscapes (Bolitzer and Netusil, 2000; Wen et al., 2015; Yang et al., 2016) also play a pivotal role in influencing housing prices. In Xiamen, a child must attend the primary school in his or her district. We chose 21 high-quality school districts, including

14 provincial-level demonstration primary schools and 7 primary schools, which also provide access to high-level secondary schools. In terms of landscape variables, we included all rivers, lakes, and bays to test their effects on housing prices. We chose a 300-meter buffer as the threshold for rivers and lakes, because in China, housing within 300 meters from the sea is considered as the first-line housing with excellent sea views. In addition, evidence shows that housing values can be lower in the proximity of urban villages. Although our dataset doesn't include the housing market within urban villages which is often informal and lacks precise statistical data, it considers the presence of urban villages in the vicinity of other housing markets. Urban villages have been created through the process of land acquisition. Farmland of villages with low compensation costs has been requisitioned and developed into new urban areas, while the residential areas of villages have been retained and transformed into informal settlements (Hao et al., 2013; Lin et al., 2014).

Table 2.1 Description of variables

Variable	Description	Mean/Proportion			
		Owner-occupied housing		Rental housing	
		Inner districts	Outer districts	Inner districts	Outer districts
Dependent variable					
Ln_THP	Logarithm of total housing price (unit: 10,000 Yuan)	5.67	5.50	7.92	7.59
Structural variables					
Area	Floor area (unit: m2)	86.05	95.98	73.61	88.82
Interior	Simply furnished (reference)	31.9%	27.2%	23.0%	18.8%
	Rough housing;	4.1%	12.4%	0.5%	1.3%
	Well-furnished house;	39.2%	43.6%	12.2%	9.6%
	Other;	24.8%	16.8%	64.3%	70.3%
Total floor	Low-rise building: Total number of floors 1–3;	0.3%	0.5%	0.3%	2.9%
	Multistory building: Total number of floors 4–6;	11.5%	11.1%	13.8%	17.3%
	Medium-high building: Total number of floors 7–9 (reference);	28.4%	14.5%	21.3%	19.2%
	High-rise building: Total number of floors >10;	59.7%	73.8%	64.6%	60.7%
Bedroom	Number of bedrooms	2.28	2.53	1.93	2.25
Living room	Number of living rooms	1.40	1.72	1.13	1.49
Building age	Age of apartment building	14.21	8.63	14.57	11.19
Locational variables					
Culture	Number of libraries culture centers within 1 km	1.91	1.45	1.82	2.21
Sports	Number of sports centers within 1 km	0.35	0.47	0.23	0.34
Hospital	Number of hospitals within 1 km	2.42	0.74	2.42	1.33
Shopping	Number of shopping facilities within 1 km	11.47	4.20	11.94	5.28
Park	Number of district-level parks within 1 km	1.04	0.84	1.02	1.21
Blue-collar jobs	Number of blue-collar jobs within 1 km (unit: 10,000)	0.96	0.39	1.01	0.57
Pink-collar jobs	Number of pink-collar jobs within 1 km (unit: 10,000)	2.05	0.20	2.21	0.33
White-collar jobs	Number of white-collar jobs within 1 km (unit: 10,000)	0.55	0.05	0.57	0.09
Bus stops	Number of bus stops within 1 km	21.64	11.17	21.36	13.89

BRT	Dummy: 1 when there is a BRT station within 1 km	0.53	0.14	0.50	0.12
Metro	Dummy variable: 1 if there is a planned metro station within 1 km;	0.76	0.44	0.79	0.51
Neighborhood variables					
River	Dummy variable: 1 if there is a river or lake within 300 meters	0.12	0.00	0.10	0.00
Seascape	Dummy variable: 1 if the sea is within 300 meters	0.03	0.19	0.03	0.13
School district	Dummy variable: 1 if it is in a high-quality school district	0.25	0.12	0.24	0.27
Urban villages	Dummy variable: 1 if there is a ViC within 100 meters	0.06	0.12	0.08	0.16

2.4 Results

Owner-occupied housing prices and rental prices in the inner districts are 26.9% and 39.1% higher than those in the outer districts. The estimated results for each submarket are shown in Table 2.2.

Structural and neighborhood variables were added as control variables to eliminate possible omitted variable bias (T. Liu et al. 2020). Regarding structural variables, our findings are similar to that of previous studies (Hu et al. 2014; Wen et al. 2014), i.e. furnished housing, more bedrooms, more living rooms, larger areas, and high-rise buildings increase house sale and rental prices, while an increase in building age lowers both prices.

Table 2.2 Regression results of OLS, SEM, and SLM

	Owner-occupied housing				Rental housing			
	Inner districts		Outer districts		Inner districts		Outer districts	
	OLS	SEM	OLS	SEM	OLS	SEM	OLS	SLM
Area	0.008***	0.008***	0.007***	0.008***	0.007***	0.006***	0.004***	0.004***
Interior (ref: simply furnished)								
Well-furnished	0.044**	0.047***	0.037**	0.043***	0.131***	0.117***	0.121*	0.104*
Other	-0.017	0.018	0.016	0.021	0.034*	0.038**	0.005	0.003
Rough housing	0.023	0.065*	-0.013	-0.016	-0.135	-0.125	-0.810***	-0.760***
Total floor (ref: Medium-high building)								
High-rise buildings	0.080***	0.104***	0.162***	0.188***	0.047**	0.041	0.071	0.068
Multistory building	0.042*	0.049**	0.023	0.01	-0.007	-0.006	0.097*	0.083*
Low-rise building	-0.450***	-0.308***	-0.024	-0.075	0.041	0.059	0.168	0.133
Bedroom	0.093***	0.087***	0.094***	0.065***	0.073***	0.085***	0.088***	0.082***
Livingroom	0.097***	0.091***	0.094***	0.065***	0.073***	0.084***	0.092***	0.085***
Building Age	0.156***	0.146***	0.131***	0.137***	0.179***	0.175***	0.151***	0.162***
Culture	0.016***	0.010*	0.021***	0.019***	0.009	0.005	0.044***	0.041***
Sports	0.024	0.025	0.056**	0.063***	0.007	-0.0002	-0.034	-0.018
Hospital	-0.017***	-0.011**	-0.01	-0.012	-0.011**	-0.011*	0.009	0.007
Shopping	-0.008***	-0.006***	0.007*	0.001	-0.002	-0.002	0.0002	0.001
Park	0.01	-0.003	-0.054***	-0.056***	-0.015	-0.016	0.001	-0.001
Blue-collar jobs	-0.059***	-0.046***	-0.079***	-0.109***	-0.039***	-0.039***	-0.081***	-0.053*
Pink-collar jobs	0.029**	0.011	0.083	0.169	-0.002	-0.004	0.258	0.198
White-collar jobs	0.051	0.107**	0.011	0.355	0.159***	0.163***	-1.601**	-1.315**

Year 2017	0.268***	0.198***	0.252***	0.144***	-0.054*	-0.060*	0.055	0.052
Bus stops	0.005***	0.003	0.009***	0.008**	-0.001	0.0002	-0.004	-0.006
BRT	-0.066***	-0.097***	0.071**	0.075*	-0.026	-0.029	0.288***	0.286***
Metro (ref: No)	0.138***	0.090***	0.090***	0.156***	0.060**	0.062**	-0.103**	-0.089**
River	-0.013	0.024	-0.08	-0.117	-0.017	-0.024		
Seascape	0.190***	0.135**	0.054***	0.070***	0.163**	0.148**	0.141***	0.125***
School district	0.096***	0.102***	-0.048	-0.053*	-0.0002	-0.001	-0.005	0.017
Urban villages	0.02	0.028	-0.039*	-0.037*	-0.03	-0.047	-0.035	-0.031
Constant	4.317***	4.444***	4.000***	4.006***	7.182***	7.169***	6.746***	5.596***
R2	0.79		0.837		0.78		0.747	
Adjusted R2	0.786		0.833		0.774		0.724	
Log Likelihood		-215.568		286.676		9.151		4.344
AIC	624.544	489.135	-324.077	-515.351	91.645	39.699	53.971	47.311

Note: *p<0.1; **p<0.05; ***p<0.01

However, the findings also show that there are similarity and diversity between housing submarkets (Figure 2.3). Differences exist between owner-occupied vs. rental markets as well as between inner-district vs. outer-district housing markets. We explain the similarities and differences in the following sections.

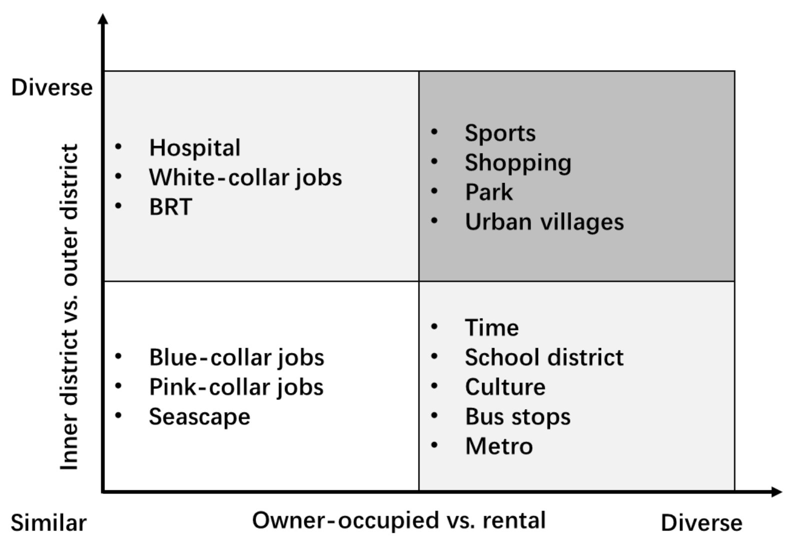

Figure 2.3 Similarity and diversity between housing submarkets

2.4.1 Similarities between submarkets

In general, the effects of amenities, jobs, public transportation, and neighborhood quality vary across housing submarkets. However, there are still some variables that have consistent effects on all submarkets, including blue-collar jobs, pink-collar jobs, and seascape. The results show a statistically significant negative relationship between blue-collar jobs and house sale and rental prices in the four submarkets. Since blue-collar jobs such as heavy industry often bring pollution and noise, they have a negative impact on house sale and rental prices (Hu et al., 2014). However, pink-collar jobs such as retails have no statistically significant effect on the prices of both owner-occupied housing and rental housing. As shown in previous studies, seascape has a positive impact on house sale and rental prices.

2.4.2 Diversities: Owner-occupied housing and rental housing

The findings show that transaction time, school district, and various amenities have a great influence on the owner-occupied market but have little impact on the rental market. Although house prices were higher in 2017 than in 2016, rents were lower. This suggests that sale prices and rental prices are inconsistent over time. We also found that a school district with a high-quality school in the inner city would increase housing prices in that district but would not increase rents. This is because only the children of homeowners, not renters, can enroll in that particular school district. Nevertheless, in the outer districts of Xiamen, a school district with high-quality schools shows a negative effect on housing prices. In the outer districts, there are two high-quality school districts which are provincial-level demonstration[2] of primary school districts. However, their surrounding environment is dilapidated and there is a lack of public facilities and amenities which is dominantly affecting the housing prices (Wang and Chen 2020). Other factors like cultural amenities, such as libraries and cultural centers, show a positive effect on housing prices, but not on rents. This may be because these facilities are related to children's education, which is a key factor that influences the decision of households on selecting owner-occupied housing. Regarding public transportation, bus stops and (planned) metro stations have a positive effect on housing sale prices but not on the rental price. Planned metro stations even have a negative impact on rental prices in the outer districts. This may be because, for many short-term tenants, metro construction has no impact on their current lives.

2.4.3 Diversities: Inner district and outer district

The results show that some variables including hospitals, white-collar jobs, and BRT have different effects on inner- and outer-district markets. The impact of hospitals on surrounding housing prices is controversial (Dai et al. 2016; Huang and Wang 2017; Li et al. 2016). In the inner districts, hospitals have a negative effect on the house sale and rental prices, since they can cause nuisance (Huang, 2017). In contrast, hospitals have no effect on both sale and rental prices in the outer districts. A possible explanation is that in the outer-district hospitals are not located in close proximity to residential areas and will have less impact on living conditions. Consistent with the findings of previous studies (Hu et al.,

[2] We select the provincial-level demonstration of primary school as the high-quality school districts and the Children living in newly built communities may also be assigned to other levels of high-quality school districts, which is ignored in our analysis.

2014), white-collar jobs in the inner districts have a significant positive effect on housing sales and rental prices. However, these white-collar jobs do not affect sale prices and even negatively affect rental prices in the outer districts. This negative effect may be caused by the fact that most white-collar jobs are mainly concentrated in the old areas of the outer districts, where the environment and buildings are relatively dilapidated which is lowering rental prices.

BRT has a positive influence on the house sale and rental prices in the outer districts—which have been built in newly developed areas with the incomplete public transportation system. BRT foremost enables people living in the outer districts to reach working places and services in the inner districts more efficiently. In contrast, BRT shows a negative impact on housing prices in the inner districts. This is because the inner-district public transportation facilities are already well developed, which leads to the lack of attractiveness of BRT. Moreover, the elevated BRT line can cause noise nuisance to the surrounding area.

2.4.4 Diversities: Across all submarkets

The results show that sports centers have a positive effect on housing prices in the outer districts, but no effect on the sale prices in the inner districts. Similar to the findings of Yang et al. (2019), the positive role of sports centers is mainly reflected in the low-end housing submarket. Nevertheless, sports centers do not impact rental prices. Contrary to our expectations, shopping facilities have a negative impact on housing prices in the inner districts. This may be related to our selection of variables, in which retail and convenience stores are part of the shopping variable. Jang and Kang (2015) found that, in comparison to shopping centers, the impact of supermarkets and convenience stores on housing prices is not significant. In addition, district-level parks have a negative impact on sale prices in the outer districts. According to Yang *et al.* (2016), there is a positive correlation between community green spaces and sale prices, but a significant negative correlation between district-level green spaces and sale prices. They argue that the reservation value of district-level public parks is higher than their use-value. In the outer districts, large parks tend to be located in areas with low population density and underdeveloped facilities, and thereby having a negative impact on sale prices. In addition, adjacency to urban villages lowers sale prices in the outer districts but does not affect sale prices in the inner districts. This may be because most urban villages in the inner districts are undergoing redevelopment and demolition. As shown in previous studies, the redevelopment has the potential to increase rather than reduce sale prices in the vicinity of urban villages (Liu et al. 2017). The results also do not support the effects of urban villages on rental prices. Although urban villages have a poor living environment, they have good access to working places as well as public facilities and services in the city. It is possible that renters pay more attention to the advantages of accessibility while giving less attention to the living environment inside urban villages due to the short-term rental.

2.5 Conclusion

Although housing submarkets have attracted increasing research interest, few studies have considered the heterogeneity of the submarket caused by different socioeconomic groups, and the inconsistency of the influence of jobs, public services, and other factors in different submarkets. This research is an attempt to widen the scope. It examines the influence of jobs, amenities, public facilities, and neighborhood qualities on four distinctive housing submarkets (owner-occupied housing, rental housing, the inner districts, and the outer districts) in Xiamen City. It gains insights into the determinants of house sale and rental prices in inner- and outer-district submarkets. The results of the hedonic price model show that these four submarkets differ substantially from each other with three main findings.

First, pollution and noise nuisance caused by blue-collar jobs can reduce house sale and rental prices throughout the city, while there is no significant effect of pink-collar jobs on sale prices. This result is consistent with the finding of previous studies that heavy industry has a negative effect on sale prices (Hu et al., 2014). Second, transaction time, school districts, and various amenities have a substantial influence on owner-occupied markets but not on rental markets. Compared to renters, homeowners compete for more educational resources and amenities (Zheng et al. 2016). As an environmental-friendly coastal city, Xiamen's seascape has also a significant positive effect on house sale and rental prices. Third, heterogeneity exists between inner-district and outer-district markets. These differences are mainly caused by spatial, economic, and historical differences. The inner districts are the commercial, cultural, historical, and geographic heart of Xiamen City, with high-quality jobs and urban services as well as dense population and construction. In contrast, the outer districts are characterized by a lack of public facilities and amenities, sparse high-quality jobs and urban services, lesser population density, and more green spaces. As a consequence, the negative impact caused by hospitals, such as traffic congestion, noise nuisance, and air pollution, are mainly impacted on high-density inner districts rather than on low-density outer districts. There is also a positive effect of high-quality white-collar jobs in the inner districts but not in the outer districts. Additionally, an efficient transportation system of BRT helps those residents living in the suburbs to commute to their working places (e.g. service sectors) in the city center, and thereby plays an influential role in house sale and rental prices in the outer districts.

These findings increase our understanding of heterogeneity across distinctive housing submarkets which are occupied by different socioeconomic groups. As 80% of migrants are renters, their housing behavior is mainly influenced by the rental market. Rental prices are less affected by the accessibility of public services and more affected by employment, labor market, and wages, implying that the most substantial barrier to trapping low-income renters is access to high-paying jobs (Li et al. 2019a). In contrast, the housing behavior of local residents is mainly affected by the housing sales market. Housing prices are mainly affected by the accessibility of public services, educational resources, and public transportation, suggesting that the main barrier to trapping low-income homeowners is access to these resources. These differences between migrant and local residents also provide evidence for the added value of identifying distinctive submarkets in the analysis of the housing market.

Furthermore, these findings also provide a basis for housing market development and spatial planning. As low-income houses in urban villages in the inner cities continues to be demolished and upgraded—which raises housing prices (Liang et al. 2019)—rental housing in the outer districts may become the mainstream market of low-income migrants in the future. They are greatly influenced by the accessibility of public transportation and facilities as well as the location of blue-collar and white-collar jobs. In the outer districts, new planning strategies could be developed to improve the public transportation system and urban public service facilities to improve the quality of life of low-income population. Additionally, for those who can afford to buy a home but cannot afford the high housing prices in the inner districts, owner-occupied housing in the outer districts is their first choice. The suburbanization of population must be accompanied by the suburbanization of employment and service facilities. Local governments and decision makers could balance the urban development by improving the suburban transportation environment and public service facilities and decentralizing employment (Li et al. 2019b).

Acknowledgements

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3. Accessibility-based equity of public facilities: A case study in Xiamen, China

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ABSTRACT

China's rapid economic development has led to inequality in terms of property, education, and health. Equal access to basic public facilities has become a key concern of inclusive development policies. However, previous studies have paid little attention to the effects of different travel modes on the accessibility of basic public facilities. The present research fills this gap. Taking Xiamen city as a case study, it explores the degrees of horizontal and vertical equity by examining the accessibility of various basic public facilities, paying attention to different travel modes and travel times. The results for Xiamen city show that disadvantaged groups experience a greater level of inequity. By taking these aspects into account, one is better equipped to identify areas in the city where access to basic public facilities is in need of substantial improvement.

***Keywords**:* accessibility, public service facilities, public transportation, equity, 2SFCA

3.1 Introduction

There has been a growing scholarly interest in the accessibility of public facilities in the past few decades (Kirby et al., 1983; Talen and Anselin, 1998; Grubesic and Durbin, 2017; Shengan et al., 2017). Good accessibility allows residents to access vital public facilities like schools and hospitals and participate in services and social interaction, while poor accessibility can lead to, or exacerbate, poor socioeconomic effects and inequality (Kelobonye et al., 2019; Lee & Miller, 2018). Therefore, examining the accessibility of urban public facilities is essential for arriving at equality in sustainable urban development and high quality of life. However, most existing studies have tended to focus on one particular facility (Apparicio et al., 2008; Fasihi & Parizadi, 2020; Grubesic & Durbin, 2017). The big advantage of focusing on one particular facility is that it can identify areas that are underserved in a certain sense and are in need of improvement in facility allocation, in other words, it can help in setting up a reasonable public facility allocation strategy. On the contrary, Tsou et al. (2005) argue that only focusing on one type of urban public facility and ignoring the relationship between public service facilities will weaken the substitution effect between public service facilities, and therefore failing to effectively measure the impact of the overall public service facilities on residents. Ashik et al. (2020) also point out that the lower accessibility of a particular urban public facility can be compensated for by the higher accessibility of another one. Therefore, it is not only necessary to allocate specific types of public facilities by disintegrated accessibility measures, but also to conduct integrated measures of accessibility that include different urban public facilities, so as to systematically identify the areas with the biggest overall shortage of services. Up till now, relatively few studies have considered a systematic approach to examining the level of accessibility of various urban public facilities (Ashik et al., 2020; Taleai et al., 2014; Tsou et al., 2005). Although these studies have provided a good starting point for measuring the integrated accessibility of various public facilities, several improvements are needed.

First, the modifiable areal unit problem (MAUP) should be considered in the spatial analysis. MAUP refers to the problem that the results of some spatial analyses (e.g., overlay analysis) depend on the choice of the areal units when point-based individual data are aggregated into areal units (Fotheringham & Wong, 1991; Kwan & Weber, 2008). Most studies on integrated accessibility use administrative or census units as the basic unit, which is quite often too large to produce accurate results. A solution can be to use smaller spatial units in order to produce more accurate results through less aggregation.

Second, studies on the integrated accessibility of public facilities have paid little attention to travel modes (Ashik et al., 2020). Although the service radius provides the basis for setting the threshold, it cannot reflect the ease of reaching public facilities. People rely on transportation when accessing public facilities, and the ease of reaching public services within the same threshold time or distance may differ under different traffic modes. Therefore, the accessibility of public facilities should consider different transportation modes. In China, the number of private cars has increased in the past few decades, but public transportation is still the major motorized mode in many cities, especially for vulnerable groups (Li, 2018). According to the Yearbook of Xiamen Special Economic Zone, in 2015 only 22.9% of the population of Xiamen city owned a private car (Xiamen Municipal Statistical Bureau, 2016). Therefore, more attention should be paid to walking and public transportation in the study of accessibility of public facilities for disadvantaged groups.

Third, research has tended to use threshold travel distance rather than travel time. For instance, Taleai et al. (2014) set different threshold travel distances for each type of public facility: At the district level, the threshold travel distance ranges from 650 to 3000 meters, and at the community level from 300 to 1000 meters. According to China's “Standard for urban public service facilities planning,” the service radius of district-level public facilities (e.g., public libraries, cultural centers, senior citizens activity centers, and public sports centers) ranges from 4000 to 7000 meters for a city with a population of 3 million (Ministry of Housing and Urban-Rural Development of the People’s Republic of China, 2018). In comparison to this broad range of service radius, travel time may better reflect the differences in time use.

Fourth, studies have mainly utilized the analytical hierarchy process (AHP) to estimate the weight for, and thus the importance of, certain urban facilities (Ashik et al., 2020; Taleai et al., 2014). Although the AHP can be used to determine the preferences for different types of public facilities from the perspective of planners and policymakers, it cannot determine the actual preferences of users for different facilities. Moreover, Iacono et al. (2008) found that for different travel modes and purposes, the coefficient of distance decay function is different. Therefore, actual travel behavior data are needed to calculate actual preferences for different types of public facilities as well as distance decay function parameters.

Lastly, little attention has been paid to vertical equity. The spatial distribution of urban facilities could be unequal due to the allocation priority to the disadvantaged or high-demand groups, leading to unequal opportunities but equal outcomes. In this regard, the policy orientation should be to narrow the gap between disadvantaged groups and advantaged groups (Cavallaro et al., 2020).

To fill the mentioned gaps, the present research investigated the disintegrated and integrated accessibility of various public facilities in Xiamen, China. We were particularly interested in the accessibility of community- and district-level public facilities and the resulting degree of horizontal and vertical equity. The methodology entails combining open data and travel survey data to analyze the accessibility of public facilities for different social groups. Open and big datasets—namely POI data on basic public facilities and commercial facilities, as well as travel time matrix data—were scraped from the online platform Gaode Map Web API by making use of the Python programming language. These data were then used to measure walking and public transportation catchment areas.

This article is structured as follows. Section 2 reviews the literature on accessibility measurements and the resulting horizontal and vertical equity. Section 3 introduces the research methodology, including the collection and analysis of several datasets. Sections 4 and 5 present the results and conclusions, respectively.

3.2 Literature review

3.2.1 Equity in the accessibility of public facilities

According to the service range, public facilities can be divided into several levels, such as city, district, subdistrict, community, and neighborhood levels (Taleai et al., 2014; Tsou et al., 2005). The service range of city-level facilities covers an entire city, whereas that of neighborhood-level facilities covers only a neighborhood. The travel costs associated with accessing these different levels of public service facilities also differ. When conducting a multicriteria analysis, Taleai et al. (2014) defined the divergent threshold distances for different levels and types of public facilities by consulting four local planners in Tehran (Iran). Since the travel distance influences the choice of travel mode, Li (2014) matched different levels of public facilities with different travel modes: 1) city and district levels correspond to public transportation; 2) subdistrict level corresponds to cycling; and 3) community and neighborhood levels correspond to walking. These differences in travel mode associated with the level of public facilities influence the accessibility of public facilities and thus the degree of equity.

There has been considerable debate about the relationship between equity and the accessibility of public facilities (Chang and Liao, 2011; Grengs, 2014). The provision of non-profit public facilities and services has a redistributive effect, that is, it "alleviate[s] to some degree the worst impacts of the wage system on the poorest groups in society" (Harvey, 1973, p. 274). Litman (2002) classifies equity into two general types, namely horizontal equity and vertical equity. The former is related to "the distribution of impacts between individuals and groups considered equal in ability and need" (Litman, 2002, p. 3). Equal groups should "receive equal shares of resources," meaning that "public policies should avoid favoring one individual or group over others" (Litman, 2002, p. 3). In contrast, vertical equity is related to "the distribution of impacts between individuals and groups that differ in abilities and needs," and transportation policies are equitable "if they favor economically and socially disadvantaged groups, therefore compensating for overall inequities" (Litman, 2002, p. 3).

Vertical equity has been applied to reveal the level of accessibility in socially disadvantaged neighborhoods (El-Geneidy et al., 2016). The findings were diverse and even contradictory in different contexts. Lucas (2012) indicates that low-income and socially disadvantaged groups often faced barriers to accessing their desired destinations. Similarly, Ricciardi et al. (2015) point out that socially disadvantaged groups comprising elderly people, low-income households, and no-care households suffer from inequitable distribution of accessibility in Perth, Australia. However, Grengs (2014) argues that vulnerable social groups in Detroit enjoy better accessibility than more privileged groups for several trip purposes, such as childcare facilities and hospitals, while the situation is reversed when it comes to accessing stores and supermarkets. In the Chinese context, some scholars identify an unbalanced spatial development of public services such as elderly care facilities (e.g., Jia et al., 2018). Others argue that low-income migrants in cities mostly live close to public facilities (Lin et al., 2011; Liu et al., 2018). These studies mainly paid attention to one specific public facility or social group, and there is a lack of research on the accessibility of various public facilities that take differences in mobility needs and abilities into account.

3.2.2 Accessibility measurements

Over the past few decades, researchers have explored the accessibility of basic public facilities with a focus on the spatial equality or inequality caused by the distribution of these services (Del Casino & Jones, 2007; Kunzmann, 1998). Accessibility can be used as an evaluation tool to direct policies for spatial equity (Panagiotopoulos and Kaliampakos, 2019). The literature addresses three key issues regarding accessibility measurements.

The first issue is the approach used to measure accessibility (Handy and Niemeier, 1997; Talen and Anselin, 1998; Tsou et al., 2005; Stanley et al., 2016). In literature, there are several common approaches, such as the container, coverage, minimum distance, travel cost, gravity, and two-step floating catchment area (2SFCA) approaches (Luo & Wang, 2003; Emily Talen, 2003). The container and coverage approaches measure the number of facilities in a given spatial unit or within a given distance from the point of origin. The minimum distance and travel cost approach to measuring the degree of closeness of facilities. The gravity approach calculates the sum of all facilities (weighted by their size or other characteristics) divided by the functional effect of their distance from the point of origin. An objection to the minimum distance and travel cost approach is that even if people choose a facility based only upon the distance, they will not necessarily choose the facility closest to their homes if they want to undertake more than one activity. For instance, if people want to undertake two or more activities, they can choose to minimize the total travel distance and travel cost, instead of choosing the activity closest to their homes. Given that a person's daily travel is comprised not only of primary but also of secondary activities, service will become more accessible when there are more opportunities.

Thus, in comparison to the minimum distance or travel cost approach, the container and the coverage approaches may be more suitable for measuring overall accessibility. Nevertheless, they have some limitations too. For example, an individual can access the facilities in adjacent spatial units. To solve this problem, a network-constrained catchment area method has been proposed. In fact, this method can be classified as a coverage approach (Miyake et al., 2010). In addition to the container and the coverage approach, the 2SFCA has been proposed. This approach can model the supply factor and the population demand factor (Luo & Wang, 2003). It estimates the supply-to-demand ratio for each public facility within a certain catchment area in the first step and sums up all supply-to-demand ratios for each population point within a certain catchment area in the second step. However, the original 2SFCA method failed to address the travel impedance factor. Therefore, an enhanced 2SFCA method—which assigns travel impedance factors using distance decay functions–was developed (Guo et al., 2019; Hu et al., 2019; Luo & Whippo, 2012; J. Wang et al., 2020; Xu et al., 2016).

The second issue relates to the accessibility measurement by travel modes. Although extensive research on the accessibility of a certain facility has considered the effect of travel modes (Arranz-López et al., 2019; Owen & Levinson, 2015), only a few empirical studies have focused on the integrated accessibility of different public facilities by different travel modes. In a city like Xiamen, the accessibility of public facilities, especially for the disadvantaged groups, should be considered by taking public transportation instead of private cars. Here, measurements by public transportation can be broadly divided into two types. Some studies measure the travel time by public transportation as the value of accessibility; they make use of public transportation routes, stops, and schedule information, and estimate travel times with the standard suite of ArcGIS Network Analyst tools (Lei & Church, 2010; Widener et al., 2015). In contrast, other studies measure accessibility by public transportation by calculating the number of public facilities within catchment areas (Grengs, 2012; Mao & Nekorchuk, 2013). In that case, they simplify the public transportation system by allowing buses to travel along the same routes as private cars, although at a slower speed. However, public transportation routes are quite often different from car routes. In addition, a public transportation passenger can only get on and off at designated stops rather than at any point along the route. In this regard, Google/Baidu/Gaode maps API can provide an origin/destination (OD) travel time matrix based on actual routes and traffic conditions for different travel modes, which is more useful than the information provided by the commonly used ArcGIS Network Analyst (Wang & Xu, 2011).

The third issue concerns the differences in preference and demand for different types of public facilities. For instance, Taleai et al. (2014) use different threshold distances for different types of public facilities based on their travel costs. In addition to the threshold time/distance, a differential weight for each public facility can be considered. Li (2014) conducted a questionnaire survey, based on which she ranked (from 1 to 7) different types of public facilities by travel frequency and importance, and then determined a weight for each type of public facility using the analytic hierarchy process (AHP method). Such approaches, however, fail to address the actual number of trips to different facilities. Another factor is the distance decay function parameter. Research by Iacono et al. (2008) shows that the coefficients of distance decay functions for walking trips are -0.094, -0.106, -0.093, and -0.100 for shopping, school, restaurant, and recreation, respectively. In terms of public transportation, they measured only the parameter of shopping trips (0.029). Their research implies that diverse decay function parameters should be measured for each trip purpose and each travel mode.

In sum, in comparison to other accessibility measurements, the enhanced 2SFCA method is considered an appropriate method for conducting integrated accessibility measurements. When measuring integrated accessibility, weights, time thresholds, and travel impedance factors for each type of public facility should be determined, because of different user preferences and demands for different types of public facilities.

3.3 Methodology

3.3.1 Study area

Xiamen is a sub-provincial city in southeastern Fujian, China. It has six districts (Siming, Huli, Haicang, Jimei, Tong'an, and Xiang'an) covering a total area of approximately 1700 square kilometers. At the end of 2015, the built-up urban area covered just over 317 square kilometers and had a population of 3.86 million (Xiamen Municipal Statistical Bureau, 2017). The urbanized area of the city has spread from Xiamen Island—where most of the city-level services and facilities are located—and especially from the southwestern coastal area to all six districts.

In terms of transportation, the household travel survey shows that non-motorized traffic, especially walking, is the main travel mode, accounting for 32.4% and 30.3% of all trips in 2009 and 2015, respectively. The proportion of trips by public transportation, including conventional buses and bus rapid transport (BRT), dropped from 31% in 2009 to

25.7% in 2015, while trips by private car (whether as driver or passenger) increased from 8.21% to 17.8% over the same period. However, public transportation remains the main motorized travel mode (Figure 3.1).

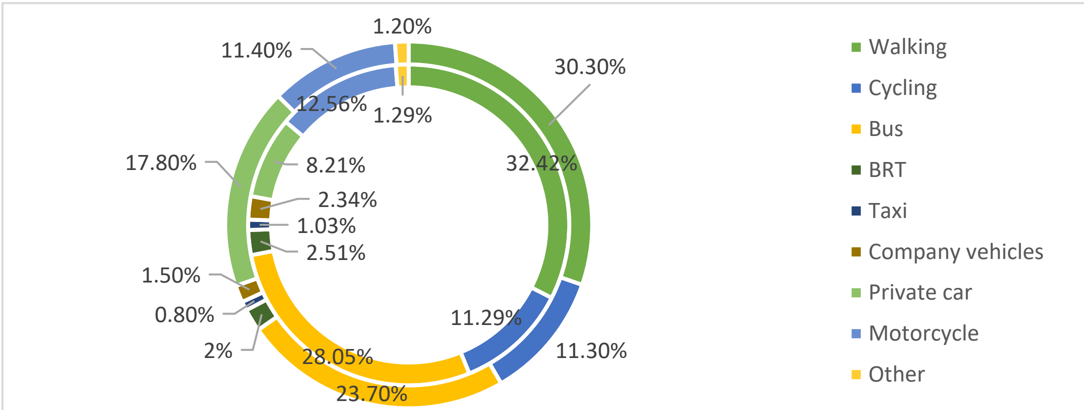

Figure 3.1 The modal split for Xiamen in 2009 (inner circle) and 2015 (outer circle) (Source: Xiamen household travel survey, 2009 and 2015)

3.3.2 Data collection and processing

We collected data that made it possible to study the geographic accessibility of basic public facilities and their correlation with socioeconomic attributes.

The 250*250 square meter grid layer and the number of residential users of China Unicom[3] for each grid were obtained from China Unicom. Since original 250*250 square meter grids produce large amounts of travel time matrix data that needs a lot of computing time, we merged 250*250 square meter grids into 1000*1000 square meter grids in order to save a substantial amount of time. For accessibility measurements, we selected urban built-up areas in Xiamen as the study area, rather than the whole administrative region, and only selected the grids with a population of more than 1,000 people. In addition, we only selected areas whose residents were included in the 2015 household travel survey.

We collected points of interest (POI)[4] data and road network data from the Gaode Map API. The GaoDe map (https://ditu.amap.com) is one of the most popular map services in China. From the POI data, we selected data on hospitals, parks, schools, senior activity centers, cultural facilities, and sports amenities. We conducted a preliminary screening of the data, including the information on basic public facilities[5]. Regarding healthcare facilities, we did identify clinics as community-level facilities and hospitals as district-level facilities. Regarding parks, we calculated their areas based on satellite data. According to the "Code for the Design of Public Park (GB 51192-2016)", parks with an area of smaller than 5 hectares were identified as community-level facilities, and parks with an area bigger

[3] China Unicom is a state-owned telecom operator and is the third-largest telecom operator in China.
[4] According to OpenStreetMap Wiki, "a point of interest or POI is a feature on a map that occupies a particular point" (http://wiki.openstreetmap.org/wiki/Points_of_interest).
[5] Urban public service facilities proposed in "Standard for urban public service facilities planning".

than 5 hectares were identified as subdistrict-level facilities (Ministry of Housing and Urban-Rural Development of the People’s Republic of China (MOHURD), 2016). Regarding schools, we did identify primary schools as community-level facilities and secondary schools as subdistrict-level facilities. Regarding senior activity centers, cultural and sports facilities, we differentiated these into different levels according to their name. For instance, the Xiange community senior activity center was identified as a community-level facility while the Xiamen city youth palace was identified as a city-level facility. We classified city-, district-, and subdistrict-level facilities into one category because these facilities are generally accessed through motorized modes of transportation, while community-level facilities can be accessed mostly through non-motorized modes of transportation (Table 3.1). The distribution of public facilities at different levels in Xiamen is shown in Figure 3.2.

Table 3.1 Different types of public facilities (Source: Ministry of Housing and Urban-Rural Development of the People’s Republic of China (MOHURD), 2016)

	Community level	City/district/subdistrict level
Healthcare	Clinic	Hospital
Park	Park	Park
School	Elementary school	Secondary school
Senior activity center	Senior activity center	Senior activity center
Culture	Cultural palace, library, recreation center	Cultural palace, library, recreation center
Sport	Sports stadium	Sports stadium

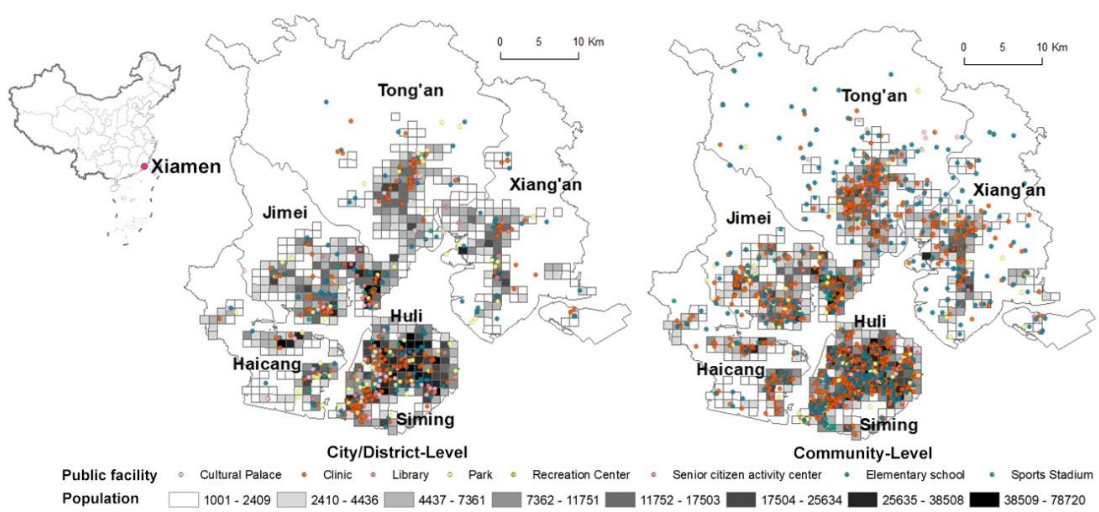

Figure 3.2 Distribution of public facilities in Xiamen (Left: city/district-level facilities; right: community-level facilities)[6]

[6] This research mainly focuses on public service facilities within the built-up area; therefore, only grids with a population distribution of more than 1000 people are selected.

Trip mode, trip purpose, travel time, and socioeconomic data were drawn from the 2015 household travel surveys. After deleting missing values and outliers, we were left with data on 39,147 households, 93,812 individuals, and 217,710 trips. Concerning the content of the datasets, data on individuals comprise age, gender, occupation, *hukou* type (family registration system), and education level. Household data comprise address, household size, car ownership, and residential housing area. Trip data comprise departure time, arrival time, trip purpose, and travel mode. Trip purpose data comprise work, education, picking up children, returning home, and business, shopping, recreational, social, medical, and other purposes. Recreational trip data comprise culture, sports, and entertainment (CSE). Travel mode data comprise walking, bicycle, electric bicycle, bus, bus rapid transport (BRT), taxi, private car, ferry, motorcycle, and other modes.

As open data sources provide real-time traffic data, which can improve the reliability of data, we developed from the Gaode API a travel time matrix for walking, public transportation, and driving. The best-path algorithm used by the Gaode API attempts to minimize the travel time from origin to destination. With the help of the Python programming language, travel distance and travel time were extracted and computed between each unit grid. In that, we set the departure time at 8:00 am, to be able to deal uniformly with the differences in the returned travel time results at different moments of time during the day.

3.3.3 Weights, threshold travel times, decay function, and high demand groups

For this research, we chose six types of basic urban public facilities, namely hospitals, parks, schools, senior activity centers, culture centers, and sports facilities. Weights and threshold travel times of various public facilities are presented in Table 3.2. The weights and threshold travel times of each type of public facility were set according to the household travel survey data. $W_{(t)}$ was determined by the frequency of each trip purpose. We included in our basic dataset trips on foot and by public transportation. In the household travel survey, cultural facilities (including entertainment) and sports facilities (CSE) are grouped in the same category of trip purpose. We divided trips for CSE by 3 to weight culture, sports, and entertainment individually.

The weights for hospitals, parks, schools, senior activity centers, and culture and sport facilities account for 0.065, 0.218, 0.656, 0.020, 0.020, and 0.020, respectively for walking; 0.196, 0.285, 0.305, 0.071, 0.071, and 0.071, respectively for public transportation; and 0.082, 0.158, 0.488, 0.091, 0.091, and 0.091, respectively for private car.

Table 3. 2 Facility types, weights, and threshold travel times (Source: (Xiamen urban planning and design research institute, 2015))

Type	Community level		District level			
	walking		public transportation		Private car	
	$W_{(t)}$	Threshold travel time	$W_{(t)}$	Threshold travel time	$W_{(t)}$	Threshold travel time

	0.411		0.348		0.241	
Healthcare	0.065	25 minutes	0.196	60 minutes	0.082	60 minutes
Park	0.218	30 minutes	0.285	70 minutes	0.158	60 minutes
School	0.656	20 minutes	0.305	35 minutes	0.488	30 minutes
Senior activity center	0.020	22 minutes	0.071	60 minutes	0.091	50 minutes
Culture	0.020	22 minutes	0.071	60 minutes	0.091	50 minutes
Sport	0.020	22 minutes	0.071	60 minutes	0.091	50 minutes

To determine the threshold travel time, we considered both the mean and the median value. However, both represent fewer than 50% of the trips. In order to cover the majority of trips, we chose the threshold travel time for each trip purpose, which covers 75% of the trips (Figure 3.3). Threshold travel time for each trip purpose and travel mode are shown in Table 3.2. Figure 3.4 presents the distance decay phenomenon for each trip purpose and each travel mode. The number of trips on foot or by public transportation for each purpose decreases as the observed travel time increases. The relationship between travel time and the number of trips for each purpose was fitted by an exponential function with different R-square values. Table 3.3 lists the high-demand groups for each type of public facility.

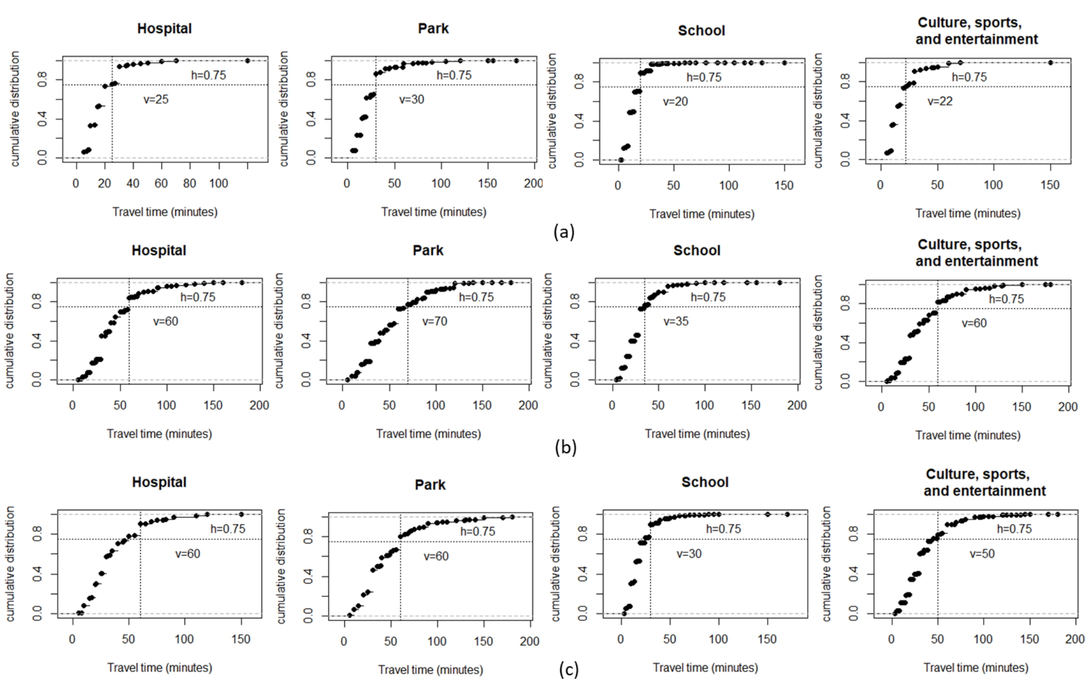

Figure 3.3 Cumulative frequency of travel time for each trip purpose (a) on foot and (b) by public transportation (c) by private car

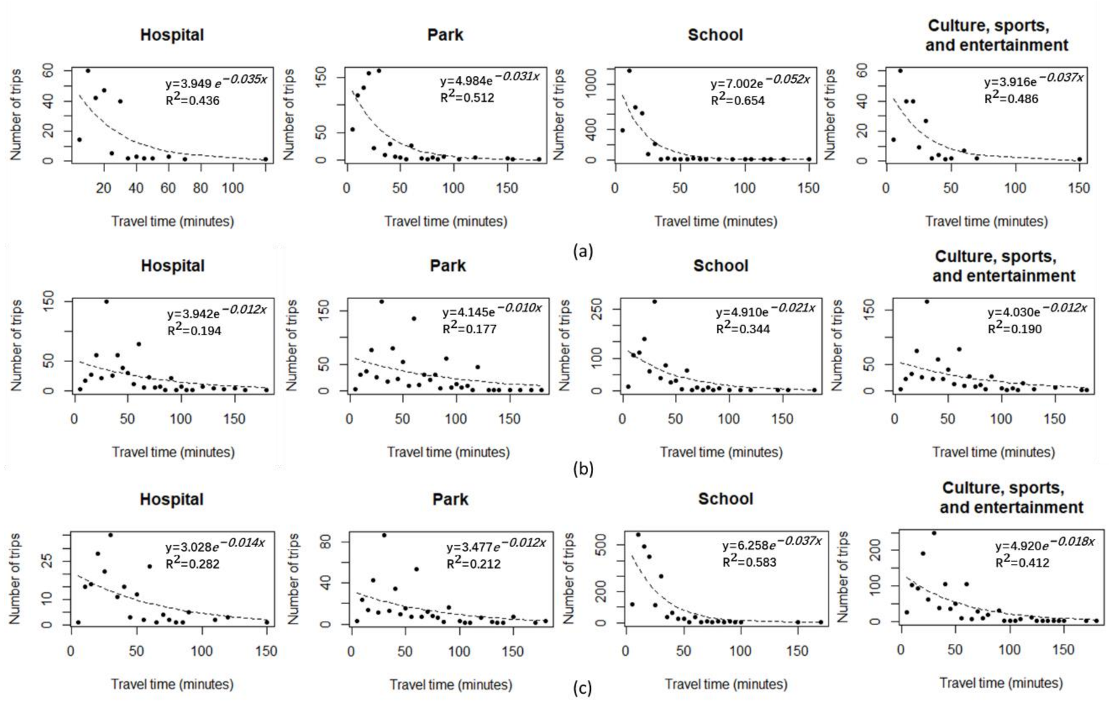

Figure 3.4 Decay function with time impedances for each trip purpose (a) on foot (b) by public transportation and (c) by private car.

Table 3.3 High demand groups for each public facility (Source: Breuer et al.2010; CIPFA, 2017; Field, 2000; Griffiths & King, 2008; Guan et al., 2019; Guo et al., 2019; Mak & Jim, 2019; Meade, 2014; National Health and Family Planning Commission of China, 2013; Pallegedara & Grimm, 2017)

	High demand groups
hospital	Children aged 0-4; women aged 15-44 (childbearing age); and seniors aged above 65
Park	Ages above 18
School	Children aged 6-12 for primary schools; children aged 13-15 for secondary school
Senior activity center	Seniors aged above 65
Culture	Ages above 18; women
Sports	People aged 5-55; male

3.3.4 Integrated spatial accessibility

We measured integrated spatial accessibility using the enhanced 2SFCA method considering: 1) supply of different level facilities, 2) accessibility by different travel modes, 3) the travel time that covers 75% of the trips, 4) difference in distance decay for each purpose, 5) differences in demands between groups, 6) differences in preference for a type of public facility, and 7) integrated spatial accessibility. We also used Microsoft SQL Server to calculate accessibility in three steps (Figure 3.5).

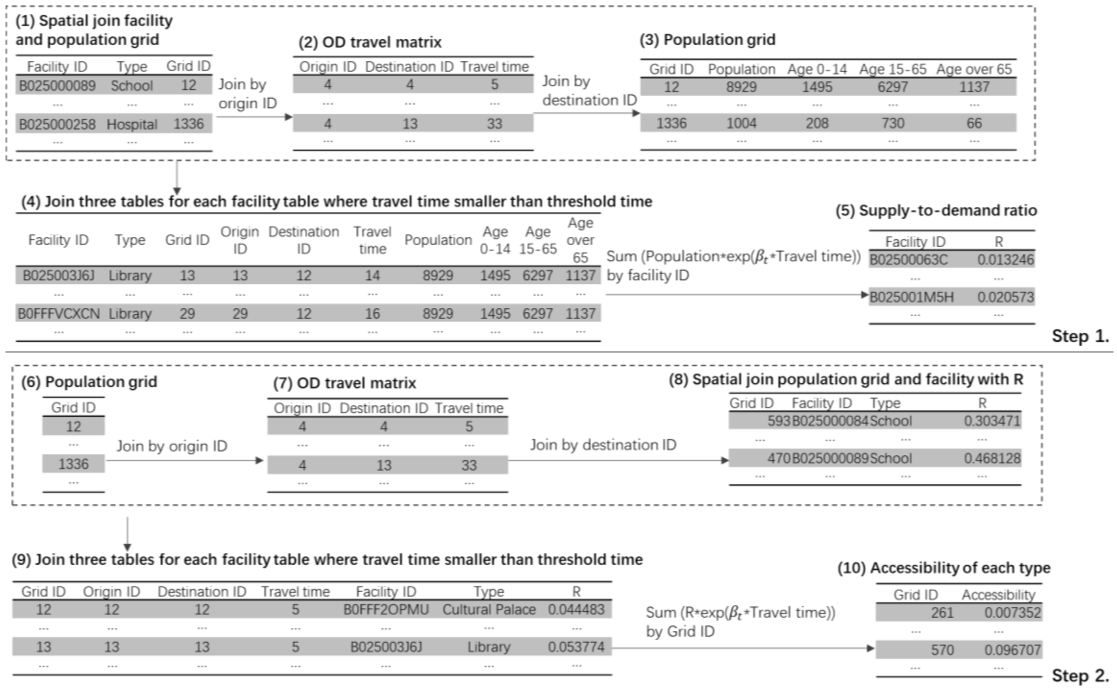

Figure 3.5. Workflow of steps 1 and 2

Step 1. Calculate the supply-to-demand ratio: First, we spatially joined public facility layers with population grid layers in ArcGIS. Second, we explored all population grids within obtained threshold travel time for each facility in SQL server. Third, we computed travel impedance based on the actual travel time between the facilities and population grids. Finally, we determined the supply-to-demand ratio R_j^t for t type facility by travel mode m:

$$R_j^{tm} = \frac{S_j}{\sum_{I \in \left\{d_{ij \leq} d_0\right\}} P_j^t f^{tm}(t_{ij})} \tag{1}$$

where S_j represents the service capacity of t type facility j. As service capacity data are not included in our dataset, we assigned service capacity for each facility according to the "Code for Urban Public Facilities Planning (GB50442-2008)", "Code for Planning of City and Town Facilities for the Aged (GB50437-2007)","Standard for Urban Residential Area Planning and Design (GB50180-2018)", and "Code for the Design of Public Park (GB 51192-2016)" (Ministry of Construction of the People's Republic of China, 2018; Code for Urban Public Facilities Planning (GB50442-2008), 2008; Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2018).

Table 3.4 Service capacity for each type of public facility (Source: Ministry of Construction of the People's Republic of China, 2018; Code for Urban Public Facilities Planning (GB50442-2008), 2008; Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2018)

	Service capacity	
	Community level	City/district/subdistrict level
Healthcare	10,000	100,000
Park	20,000	100,000

School	15,000	50,000
Senior activity center	50,000	500,000
Culture	10,000	200,000
Sport	10,000	100,000

P_j^t is the population high-demand groups for t type of facility at location i within the threshold travel time of j ($d_{ij\leq}d_0$). $f^{tm}(t_{ij})$ is the decay function of travel time for t type facility by travel mode m:

$$f^{tm}(t_{ij}) = e^{\beta^{tm}t_{ij}}$$

where β^{tm} means the decay coefficient for t type facility by mode m and t_{ij} represent travel time between location i and location j.

Step 2. Compute the accessibility value: We explored all facilities within a certain threshold travel time for each population grid. Then compute travel impedance based on the travel time between the population grids and facilities. After that, sum up the supply-to-demand ratios R_j^t travel impedance to calculate accessibility value A_i^{tm} for t type of facility.

$$A_i^{tm} = \sum_{i\in\{d_{ij\leq}d_0\}} R_j^{tm}\, f_t(t_{ij})$$

Step 3. Determine the integrated spatial accessibility: We calculated the integrated spatial accessibility based on the weighted sum of all types of public facilities at population grid i.

$$A_i^m = \sum_{t=1}^{n} W_t^m\, A_i^{tm}$$

A_i^m is the integrated spatial accessibility at residential location i by m type of travel mode W_t^m represents the weight t type of facilities by m type of travel mode.

$$A_i = W^w A_i^w + W^p A_i^p$$

Where W^w and W^p are the mean weights on foot and by public transportation (or private car), respectively. A_i^w and A_i^p represent integrated spatial accessibility at residential location i on foot and by public transportation (or private car), respectively.

3.4 Results

3.4.1 Horizontal equity

Figures 3.6 and 3.7 illustrate the disintegrated and integrated accessibility to urban facilities in Xiamen city. With respect to the disintegrated accessibility, each type of public facility has different degrees of accessibility. The spatial accessibility of community-level healthcare, parks, and cultural facilities has a polycentric structure. For most types of community-level public facilities (including healthcare, park, school, and culture), the central area of Siming District and the old towns of Tong'an and Xiang'an Districts enjoy relatively higher accessibility. For Siming District, this is mainly due to sufficient supply (see Figure 3.8(a)), while for Tongan district and Xiang'an District, this is mainly due to reduced demand (see Figure 3.8(b)).

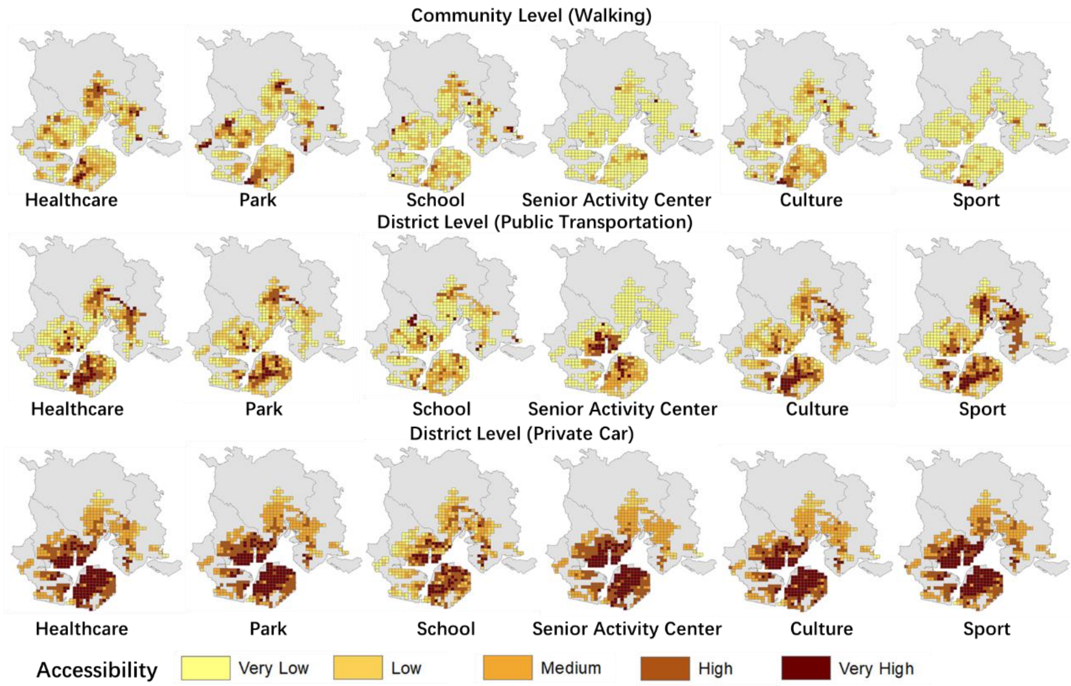

Figure 3.6 Disintegrated accessibility

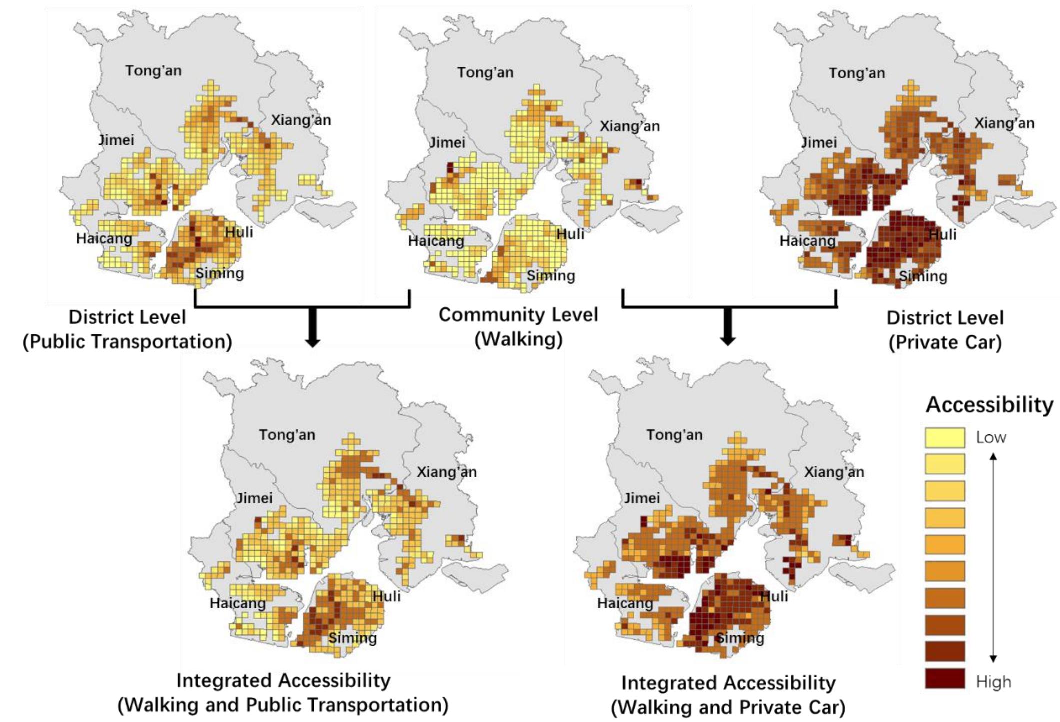

Figure 3.7 Integrated accessibility by walking and public transportation (WP) and walking and private car (WC)

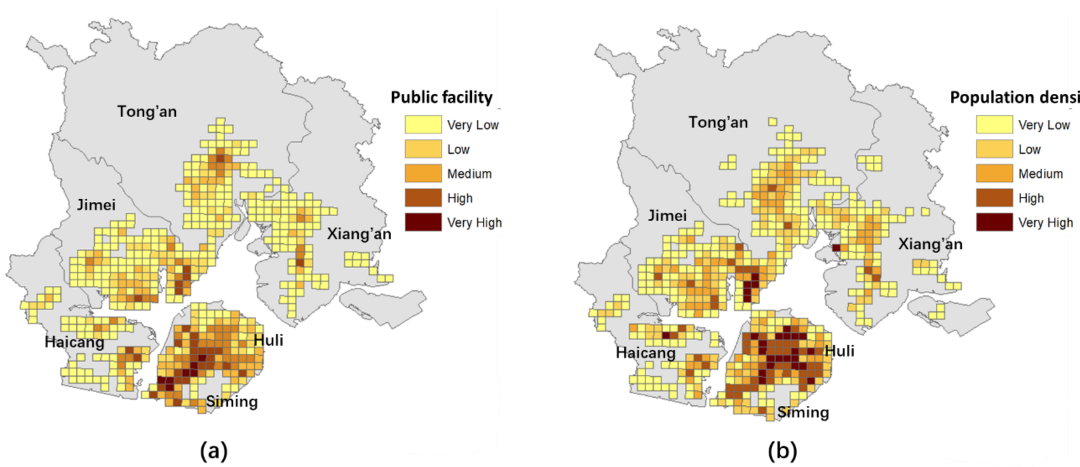

Figure 3.8(a) Distribution of public facilities (b) population density

Interestingly, the accessibility of district-level hospitals, parks, and cultural and sports facilities by public transportation present a corridor structure. This corridor structure can be attributed to the public transportation services by which different centers are connected. However, these public transportation services show to have no significant effect on the accessibility of schools and senior activity centers at the district level. A possible explanation for this is that shorter time thresholds for schools have weakened the role of public transportation.

With respect to integrated accessibility, there are differences between the spatial accessibility of community-level public facilities and district-level public facilities. Low supply and high demand have led to low accessibility of community-level public facilities in Haicang, Jimei, Tong'an and Xiang'an districts near Xiamen Island. In contrast, the relatively efficient public transportation system in these areas has resulted in higher accessibility to district-level public facilities by public transportation. In terms of accessibility by car, the closer one is located to Xiamen Island, the better is the accessibility of district-level public facilities. Compared with the public transportation system, private cars can greatly improve the accessibility of public services. Two types of integrated accessibility were calculated. One is for people who do not have a private car. These people can access community-level public services on foot and city-level public services through public transportation; the other is for people who own private cars, who can access community-level public services on foot and city-level public services through private cars. Figure 3.7 implies that owning a private car can greatly improve the accessibility of public service facilities.

3.4.2 Vertical equity for different social groups

Litman (2002) divided vertical equity into: 1) "vertical equity with regard to income and social class", that is, "the distribution of impacts between individuals and groups that differ by income or social class"; and 2) "vertical equity with regard to mobility need and ability," namely "the distribution of impacts between individuals and groups that differ in transportation ability and need" (p. 3). To integrate sociodemographic variables and mobility needs and ability into a small number of factors, a factor analysis method can be used, in which the explained variances indicate the relative importance of different factors (Wang & Luo, 2005).

Based on a literature review and existing data (Wang & Luo, 2005), this study considered the following variables—all of which were derived from the 2015 Xiamen household travel survey data—namely, *hukou* status, education level, homeownership, low-skilled, and car ownership. The analysis was conducted using the principal axis factoring with the Varimax rotation technique. The factor analysis generated 2 factors with eigenvalues greater than 1 (Table 3.5). The Kaiser-Meyer-Olkin (KMO) value is higher than 0.5, which is acceptable.

Table 3.5 Rotated factor loadings (pattern matrix) and KMO

	Factor 1: socioeconomic disadvantages	Factor 2: educational disadvantages	KMO
Migrants (%)	0.9508	-0.0529	0.6154
Without high school diploma (%)	-0.0619	0.8533	0.6266
Renters (%)	0.9707	0.0147	0.5416

Household without cars (%)	0.6427	-0.6409	0.6886
Low-skilled groups (%)	0.0548	0.8797	0.6288
% of variance explained	45.33	38.32	
% of variance explained by the 2 factors	54.19	45.81	

Factor 1, which accounts for 45.33% of the total variance, mainly captures three variables: migrants, renters, and households without cars. This factor is mainly related to the non-local population, who are disadvantaged in terms of social welfare, housing, income, etc. As expected, areas with high scores are concentrated in urban villages—regarded as the clusters of migrants—in Huli, Haicang, and Jimei districts (Figure 3.9(a)). Factor 2, which accounts for 38.32% of the total variance, mainly captures two variables: without high school diploma and low-skilled groups. Areas with high scores are concentrated in the outer areas of the city, where most of the population is composed of local villagers (Figure 3.9(b)).

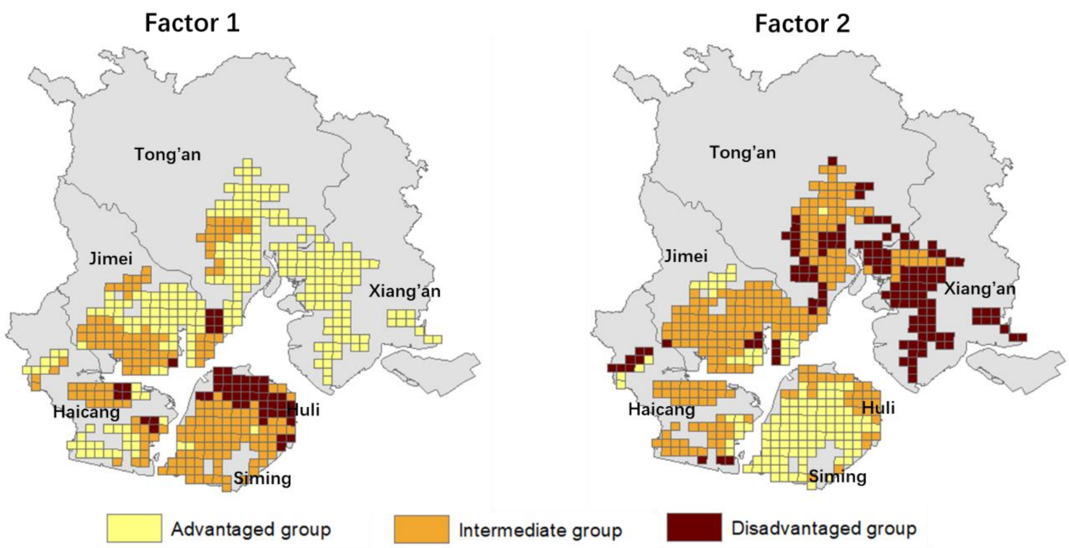

Figure 3.9 The scores of (a) socioeconomic disadvantages (b) educational disadvantages

As demonstrated in Figure 3.10, the accessibility of disadvantaged groups is lower than that of advantaged groups, regardless of whether they live in the inner area or the outer area. In general, people living in the inner area enjoy higher accessibility than those living in the outer area. Owning a vehicle can greatly improve accessibility, and WC-based integrated accessibility is twice that of WP-based integrated accessibility. For the first type of disadvantaged groups, 80% of them do not have a car, therefore having more difficulty in accessing public services than the advantaged groups. The existence of a large number of urban villages within the island allows them to settle within the island, and thus they enjoy higher accessibility than those living in the outer area. However, a large number of urban villages in the inner area are facing demolition, so this group may face displacement and experience the greatest injustice in the future. Regarding the second vulnerable group (most of whom are local residents living in the outer area), about 60% of them enjoy high accessibility by car, while only 40% of them have the lowest accessibility. Overall, those disadvantaged groups who live in the outer area without a vehicle have the lowest accessibility. To some extent, this suggests that vertical inequality is worse than horizontal inequality.

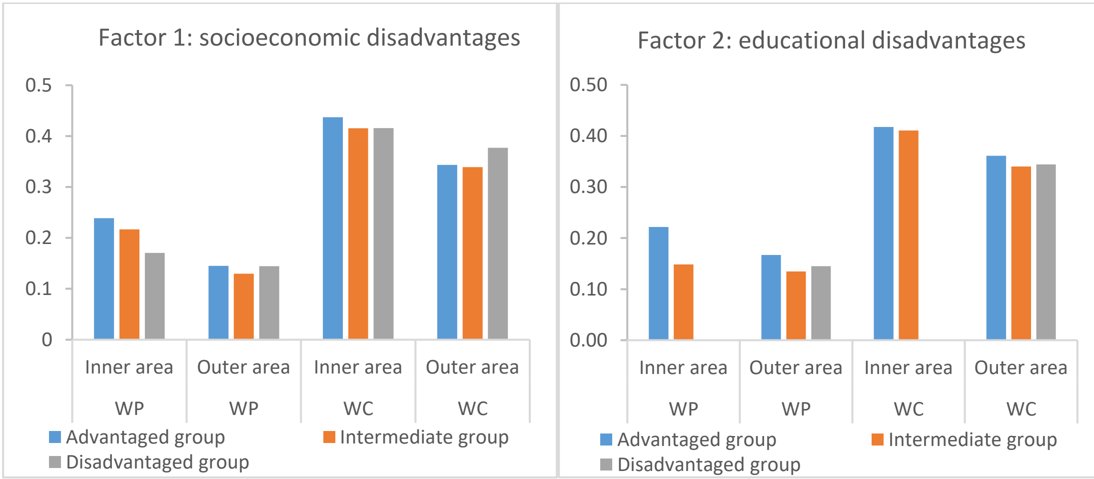

Figure 3.10 Vertical equity by (a) socioeconomic disadvantages (b) educational disadvantages

3.5 Conclusions

The present research contributes to international studies on the relationship between equity and the accessibility of public facilities. Previous studies paid little attention to the accessibility of various public facilities, the effects of different travel modes, and the interaction between different kinds of facilities (Ashik et al., 2020; Fasihi and Parizadi, 2020; Grubesic and Durbin, 2017). This research fills that gap. Taking Xiamen city as a case study, it measured the disintegrated and integrated accessibility of various public facilities by considering different travel modes. Compared with existing studies on integrated accessibility, the present research used smaller spatial units for the measurements in order to produce more accurate results and prevent the indicated MAUP problem. Besides, the research paid attention not only to the threshold travel distance but also to the travel time, which better reflects the differences in the accessibility of public facilities for certain population groups. It incorporated actual travel behavior into predefined thresholds, weights, and travel impedance factors. The thresholds were based on analyzing the cumulative frequency of actual travel time for each purpose, ensuring a 75% coverage rate. The weights were determined by travel frequency for each purpose. Although some previous studies also established integrated measurements of urban public facilities (Taleai et al., 2014; Tsou et al., 2005), basing calculations on data from the travel survey is a step forward, since it is more in accordance with actual travel behavior.

Specifically, the present research explored horizontal and vertical equity by examining the accessibility of community- and district-level public facilities in Xiamen city. Vertical equity was assessed by examining the integrated accessibility in terms of advantaged, intermediate and, disadvantaged groups. The results show that the degree of vertical inequality is generally higher than that of horizontal inequality, indicating that disadvantaged groups experience a greater level of inequity. In particular, disadvantaged groups living in outer areas without access to vehicles experience the greatest inequities. It is worth noting that many urban villages in the inner areas are facing demolition, and many disadvantaged groups currently living in the inner areas are facing relocation. In order to alleviate the inequity in their access to public service facilities, on the one hand, the supply of a certain proportion of low-rent housing in the inner areas should be guaranteed; on the other hand, the accessibility of public transportation in the outer area with a high concentration of disadvantaged groups should be improved, so as to improve their overall accessibility.

In sum, this research provides new insights into different methods with which to identify specific places where public transportation or public facilities need to be improved based on people's demands. The results of disintegrated accessibility identify the areas without sufficient supply of specific types of public facilities. Measuring the difference between horizontal and vertical inequality can help identify areas where integrated accessibility of public facilities needs to be significantly improved. The identified accessibility provides information that can help planners to determine the appropriateness of existing public transportation facilities to and/or basic public facilities for certain socioeconomic groups in different areas of a city. Based on these insights, policymakers can enhance the equitable distribution of public transportation facilities to and/or basic public facilities at the spatial level and thus promote more equal access to public facilities. However, there are still some limitations of this study. On the one hand, POI data did not cover all data. For those facilities with a small number (such as senior activity centers), the omission of a point might have a big impact on the results. On the other hand, although income is an important factor in identifying disadvantaged groups, we did not consider this factor due to data limitations.

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4. Spatial mismatch for distinct socioeconomic groups in Xiamen, China

ABSTRACT

Studies have found that spatial mismatch is a universal phenomenon, although both their substantive and their methodological focus can differ substantially. In China, there is a growing body of literature on spatial mismatch. However, most research on spatial mismatch in China does not distinguish between subgroups, such as local and migrant workers. The present research investigated the spatial mismatch for different socioeconomic groups in Xiamen according to their *hukou* status, which is an indication of their local/migrant status. As one of the country's first Special Economic Zones (SEZ), Xiamen experienced housing marketization much earlier than- most other Chinese cities and at the same time attracted a large amount of capital and a large influx of migrants. The findings show that blue-collar, pink-collar, and white-collar workers, who are further categorized as either locals or migrants, experience varying degrees of job accessibility and spatial mismatch. Furthermore, the findings show that even though migrant workers experience less spatial mismatch, they still experience disadvantages in terms of commuting time due to their dominant travel mode. The results presented in this paper are helpful for understanding the spatial mismatch for various socioeconomic groups and facilitating sustainable mobility and social equity.

Keywords: spatial mismatch, job accessibility, blue-collar, pink-collar, white-collar, local and migrant workers, Xiamen

4.1 Introduction

A number of studies on spatial mismatch have been published since Kain (1968) investigated in the United States how, in the 1960s, the spatial mismatch between blue-collar suburban jobs and inner-city African Americans led to long-distance commuting by and rising unemployment among the latter (Bi et al., 2019; Hu, 2015; Liu & Kwan, 2020). Most current research on spatial mismatch focuses on European or American cities, or on Chinese megacities, such as Beijing (e.g., Huang et al., 2019). However, the theories and findings of these studies may not be directly applicable to other Chinese cities, because the contextual conditions can be very different. For instance, in the United States certain ethnic groups experience a much higher spatial mismatch than whites, since the former are more likely to reside in inner cities (Easley, 2018), while low-skilled blue-collar jobs continuously decentralize toward suburbs and exurbs (Stoll, 2006). In contrast, disadvantaged groups in China, such as migrant workers, are not the groups that experience the greatest spatial mismatch. For example, Huang et al. (2018) found that in Beijing many migrants easily adapt to their new circumstances by changing jobs to reduce their degree of spatial mismatch. However, until now, the spatial mismatch for various socioeconomic groups in large Chinese cities (other than megacities) has not been investigated explicitly. To fill this gap, the present research examined the spatial mismatch for distinct socioeconomic groups in Xiamen city, because this large city was one of the first places where the danwei system collapsed as a result of the economic reform. Danwei—or work unit—refers to an institution that provides urban residents with housing and educational, cultural, health, and other welfare facilities (Chai, 1996). The disintegration of the danwei system is often seen as one of the main reasons for spatial mismatch in China (e.g., Fan et al., 2014; Liu and Chai, 2015). In 2015, only 1% of the population of Xiamen were still living in danwei housing (Xiamen urban planning and design research institute, 2015).

When studying spatial mismatch, the first step is to measure the degree of spatial mismatch. Methods to calculate this degree can be broadly summarized into three categories, namely those that use 1) commuting time/distance, 2) the dissimilarity index, or 3) job accessibility (Qi & Fan, 2018). For commuting time/distance, one can analyze the relationship between independent variables and commuting time at the individual level. However, these calculations cannot describe spatially which locations have the greatest spatial mismatch. In the case of the dissimilarity index, one describes the degree of imbalance between jobs and housing within a region or city (Hua et al., 2017). However, as Hu (2015) argued, this index does not indicate the spatial disparities at the disaggregated level. In this regard, the third measurement—job accessibility—is usually employed (e.g., Hu, 2015; Hua et al., 2017).

In the study of social equity, spatial mismatch emphasizes the imbalance in the distribution of disadvantaged groups and employment, and job accessibility is used as an indicator to determine the extent to which workers can access jobs by a certain travel mode within a fixed time threshold (Fan et al., 2014). However, this method does not consider competition between subgroups. For example, if there are 1,000 blue-collar jobs available and 1,000 blue-collar local workers and 1,000 blue-collar migrant workers, the supply (i.e., blue-collar jobs) and demand (i.e., local blue-collar workers) are regarded as balanced, ignoring the competition from blue-collar migrant workers and the resulting spatial mismatch. In order to solve this deviation in the calculation of spatial mismatch when certain types of jobs or workers are divided into subcategories, in the present research the dissimilarity index was optimized so that it could indicate the spatial disparities of local and migrant workers.

This paper is structured as follows. Section 2 reviews spatial mismatch for different socioeconomic groups in China. Section 3 describes the data sources and methodology, including the data collection and management, as well as the implementation of a geographic information system (GIS). Section 4 presents the results of the analysis; that is, the spatial mismatch for different socioeconomic groups in Xiamen city. Section 5 concludes the paper and discusses policy implications.

4.2 Literature review

4.2.1 Spatial mismatch in China

Spatial mismatch refers to the discrepancy between where people work and where they live. The first study on spatial mismatch explored how the suburbanization of jobs contributed to high levels of unemployment among African Americans living in inner cities (Kain, 1968). There is renewed policy interest in spatial mismatch issues in China, since emerging research shows that spatial mismatch is a growing problem. Several potential causes of this have been identified.

Some scholars have pointed to the disintegration of the danwei system as one of the main causes of spatial mismatch in China (Fan et al., 2014; Liu & Chai, 2015). Before the housing reforms in 1998, danwei provided people with not only employment but also housing and various facilities. Life within the danwei system was convenient, as employees' economic, political, and social lives were all within the walls of their danwei community (Li & Kleiner, 2001). As jobs and housing were well balanced in this system, commuting distances were relatively short (Chai, 1996; Chai et al., 2011; Xu, 2011). The disintegration of the danwei system as part of the housing reforms separated economic activities from individuals' daily activities, leading to spatial differentiation and dispersion (Chai et al., 2011). As a consequence, growing numbers of urban residents bought houses in the private market, which resulted in a further separation of workplace and place of residence (Chai et al., 2007).

Another potential cause of spatial mismatch is the large-scale urbanization and subsequent suburbanization that has arisen as a result of China's market-oriented economic reforms. The eastern coastal cities and special economic zones (SEZs) that were opened up to overseas investment during the 1980s became new places of economic growth and population concentration. Since then, these coastal cities—which include Xiamen—have attracted millions of mostly rural migrants to work in the newly established manufacturing industries (Liu & Chai, 2015). The proportion of migrants in eastern Chinese cities increased from 38.48% in 1982 to 64.60% in 2005 (Duan & Yang, 2009). Cities expanded into huge industrial sites, leading to drastic spatial restructuring (Liu & Chai, 2015). Over the last 10–15 years, there has been a decentralization (suburbanization) of industry and construction jobs from central business districts to the outskirts of cities due to much cheaper land prices, while the rapidly growing service sector has quickly filled the leftover spaces in the central business districts.

The rapid expansion of these SEZs and eastern coastal cities has caused varying degrees of spatial mismatch between different types of workers and their corresponding jobs. As Kain (1968) indicated, the level of spatial mismatch varies between occupations and industries. In Kain's findings, this difference is mainly reflected in blue-collar jobs (e.g., those performed by craftsmen, machine operatives, and laborers) and "other" jobs (e.g., managerial, technical, official, professional, clerical, and sales jobs). Unequal spatial distribution of skill requirements and residential segregation exacerbates this mismatch. Similarly, Fan et al. (2014) found that the level of spatial mismatch in Beijing varies between occupations. Specifically, the spatial mismatch for blue-collar workers is greater than that for pink-collar workers.

Another important finding by Fan et al. (2014) is that the spatial mismatch for migrant workers is greater than that for local workers. In the past, the urban household registration system (hukou) limited inter-city population flows (Chai, 1996). Housing reforms coupled with rapid urbanization have prompted a massive influx of migrants into these SEZs and eastern coastal cities. These migrant workers, who do not possess local hukous, cannot access the government-subsidized affordable housing system (Fan, 2010). Consequently, a big distinction emerged between local workers and migrant workers in terms of housing and job accessibility. Low-income local workers can apply for affordable public housing, which is mainly located on the urban fringes and has poor access to jobs and facilities (Zhou et al., 2013). In contrast, most low-income migrants are legally excluded from affordable public housing in the city and have to rent private homes, notably rooms, in "urban villages," which are often located quite close to and/or incorporate low-income job opportunities and other facilities (Hao et al., 2012, 2013; Lin et al., 2014). Other reasons for migrants to rent housing in urban villages are the low rents and the "network effect" of being well-informed of work opportunities (Zhu et al., 2017). This all suggests that different *hukou* holders settle in different parts of the city and experience distinct forms and degrees of spatial mismatch.

Given these differentiations within the phenomenon of spatial mismatch, following Qi et al. (2018) in the present research we defined spatial mismatch as a mismatch for any specific population group between where they live and where their suitable and accessible job opportunities are located. In this, we took into account that spatial mismatch is population-specific and is sensitive to the accessibility by transportation and to the skill level of the specific population group under study. Differences between occupations (e.g., blue-collar, pink-collar, and white-collar jobs) and between *hukou* status (e.g., local population versus migrant population) may cause differences in the degree of spatial mismatch (Fan et al., 2014). Therefore, we distinguished different groups based on occupation and hukou. Blue-collar workers perform non-agricultural manual labor in, for example, manufacturing, mining, construction, mechanical engineering, maintenance, or warehousing, whereas pink-collar workers perform service-oriented clerical jobs, such as customer interaction, entertainment, or sales (Fan et al., 2014). White-collar workers have high-education occupations; they work in offices or other administrative settings, doing professional or administrative work.

4.2.2 Measurement of spatial mismatch

Several attempts have been made to use commuting time to test the spatial mismatch hypothesis (e.g., Haddad, 2020; Zhao et al., 2011). These studies were generally based on individual-level commuting data derived from surveys, and used statistical analysis (e.g., regression models) to measure the impact of different independent variables on commuting time. Research that took commuting time as the dependent variable can be subdivided into two categories. The first category uses job accessibility as an independent variable to study its impact on commuting time (e.g., Zhao, 2015), while the second category uses travel time as an indicator of spatial mismatch in analyzing whether a specific group has a longer travel time than other groups (Haddad, 2020; Zhou et al., 2016). These studies analyze and compare the relationship between independent variables and commuting time at the micro level, but fail to describe which locations have the greatest spatial mismatch.

Another commonly used indicator for spatial mismatch is the dissimilarity index. This index was traditionally used to measure the degree of housing segregation between different races within a city or region, and was later used in the study of spatial mismatch to measure the imbalance in the housing and jobs of disadvantaged groups. For instance, Liu and Painter (2012) used the dissimilarity index as a measure of spatial mismatch to measure the imbalance between residential and employment distribution. Qi and Fan (2018), however, argued that the original index—which assumes that spatial interaction does not depend on distance or that spatial interaction will continuously decrease as distance increases—was problematic for measuring the spatial mismatch for disadvantaged groups in China, whose main commuting mode is public transportation. They therefore extended the dissimilarity index by measuring the imbalance between residential distribution and employment that is accessible by public transportation. However, while the index can calculate the overall degree of spatial mismatch in a large region, it cannot indicate the spatial disparities disaggregatedly.

A third commonly used indicator is job accessibility, which identifies the degree of spatial mismatch for each spatial unit. Among the numerous accessibility calculation methods, Shen's (1998) relative gravity-based job accessibility model is the most commonly used in studies of spatial mismatch (e.g., Hu, 2015; Hua et al., 2017). This is because Shen’s measures incorporate all three factors of spatial mismatch, namely the location and number of vulnerable groups, the location and number of their jobs, and the commuting time between the two locations. However, as described in the introduction, although this method is effective when the total number of jobs and the total number of workers are roughly the same, a certain degree of calculation bias will arise in the case of subcategorization.

To address the spatial mismatch problem when certain types of jobs or workers are further divided into subcategories, we optimized the dissimilarity index so that it can not only measure the spatial mismatch for a certain subcategory of workers, but also reflect the spatial disparity in a larger range.

4.3 Methodology

4.3.1 Study area

Xiamen is a hub city in the southeast of Fujian Province. It has six districts: two inner districts (Siming and Huli) and four outer districts (Haicang, Jimei, Tong'an, and Xiang'an). The urbanized area has spread from the original island (Siming and Huli districts) to the other four districts; between them, the six districts cover nearly 1,700 square kilometers (Figure 4.1). The Xiamen Special Economic Zone (SEZ) was one of the first of initially four SEZs to be created as part of China's opening up process in the early 1980s. In 1980, the State Council approved the establishment of a 2.5 square kilometer SEZ in Xiamen. After China's then-paramount leader Deng Xiaoping visited Xiamen in 1984, the SEZ was extended to cover the whole island (131 square kilometers). The State Council then successively approved the establishment of Taiwanese investment zones in Haicang, Xinglin, and Jimei, and implemented the existing policies for the SEZs. In 1992, it also approved the establishment of the Xiangyu Free Trade Zone.

In 2017, the population of Xiamen reached 4 million people, of whom 2.3 million held Xiamen local hukous, enabling them to enjoy various benefits. For instance, their children can be enrolled in public schools; they are eligible to apply for affordable housing and low-rent housing and for entrepreneurial interest-free loans; and they get high-value medical social insurance and welfare. Migrants without local hukous do not enjoy these benefits (Hua et al., 2017).

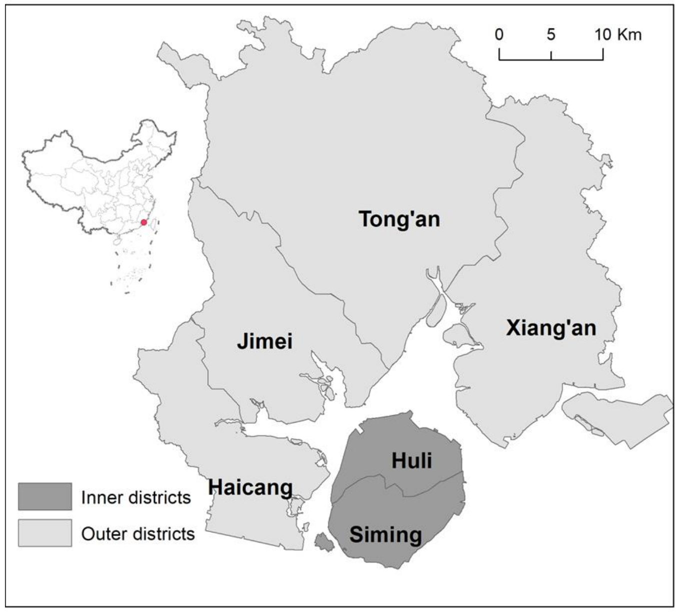


Figure 4.1 Districts and areas of Xiamen City

4.3.2 Data collection and classifications of different socioeconomic groups

Travel time matrix data (real-time travel data) were obtained from the Gaode Maps application programming interface (Gaode API), which is a set of application programming interfaces written in JavaScript. It contains basic functional interfaces for building maps and providing data services, for example, for local search and route planning. In order to deal with the differences in return time results at different times of the day, we set the departure time at 08:00. We used a 1000*1000 square meter grid as our basic unit, and obtained the travel time matrix between each unit from the Gaode API. We chose the urban built-up area of Xiamen as the research area, rather than the entire administrative area, and only selected grids with a population of more than 1,000 people.

Socioeconomic and travel data were drawn from the 2015 Xiamen household travel survey. These data cover 3% of the total population of Xiamen and include trip mode, trip purpose, travel time, origin, destination, etc. Socioeconomic data include age, gender, occupation, education level, housing attribute, car ownership, etc.

Previous studies often used income, education level, and skills as indicators of disadvantaged workers (Fan et al., 2014; Hua et al., 2017). In line with the classification developed by Fan et al. (2014), we divided jobs and workers into blue-collar jobs/workers, pink-collar jobs/workers, and white-collar jobs/workers. Both blue-collar and pink-collar workers are regarded as having low-education occupations. Blue-, pink-, and white-collar workers comprised 16%, 31%, and 53%, respectively, of our sample.

Employment data for 2012, comprising 65,891 firm records and 2,026,217 job records, were obtained from Xiamen Municipal Bureau of Commerce. The jobs were categorized into 19 economic sectors and then were further categorized into agricultural, blue-collar, pink-collar, and white-collar jobs, based on the classification developed by Fan et al. (2014). In our data, blue-, pink-, and white-collar jobs comprised 56%, 32%, and 12%, respectively, of the jobs.

4.3.3 Measuring job accessibility

To measure job accessibility, we applied a cumulative opportunity approach (Geurs & van Wee, 2004; Hernandez, 2017), which defines travel mode and travel time, and then counts the number of jobs reachable via that mode within that travel time. This approach uses ArcGIS, Python, and MySQL for data collection, analysis, and management. It comprises five steps.

Step 1: Define travel mode, threshold travel times, and decay function

In Xiamen, walking and public transportation are the dominant travel modes, accounting for 30.3% and 25.7%, respectively, of all trips in 2015. Cumulative frequency analysis showed that 75% of the working population traveled for less than 50 minutes by public transportation and less than 20 minutes on foot. We therefore defined the threshold time as 50 minutes for public transportation and 20 minutes for walking (Figure 4.2). We calculated different distance-decay coefficients for walking and public transportation, as shown in Figure 4.3.

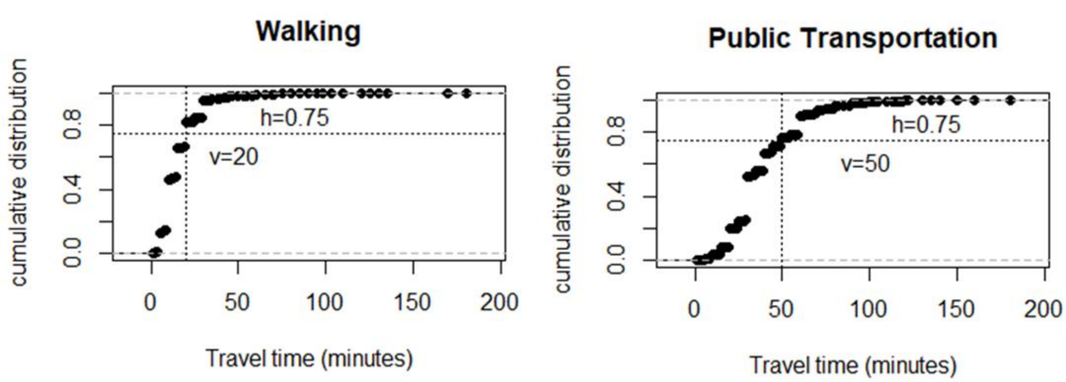


Figure 4.2 Cumulative frequency of travel time for (a) walking and (b) public transportation

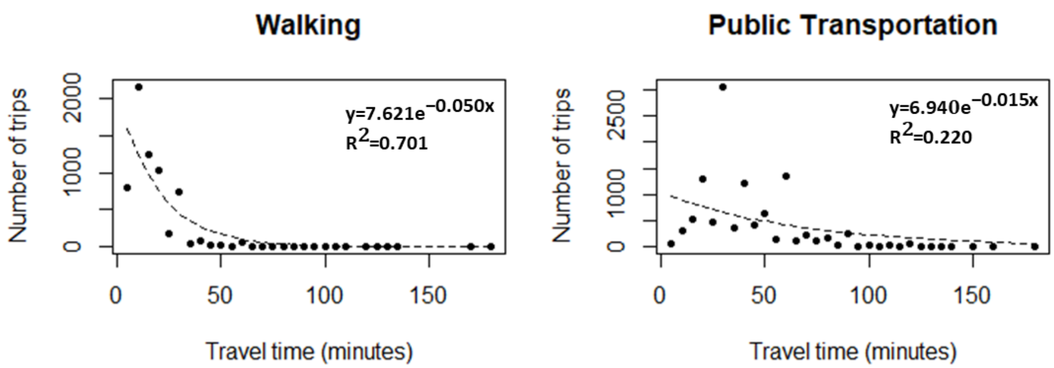


Figure 4.3 Decay function with time impedances for (a) walking and (b) public transportation

Step 2: Define the basic unit within a GIS environment

Previous studies used traffic analysis zones (TAZ) or administrative districts (*jiedao*) (Fan et al., 2014; Hua et al., 2017) as their basic units. However, the average size of a TAZ in Xiamen is 9.2 square kilometers, which is too big to produce accurate results. Apparicio et al. (2008) concluded that in order to increase accuracy, smaller spatial units should be used. Consequently, and as mentioned, we used 1000*1000 square meters as the basic spatial unit in our analysis. We only selected populated built-up areas as research units, since it would have been meaningless to measure accessibility for non-built-up areas (or areas without a population).

Step 3: Obtain travel time matrix by using Python and MySQL

In order to measure the travel time by different transportation modes, we used the Python programming language to collect the travel time matrix data for different transportation modes from the Gaode Maps (AMap) Geocoding API. We calculated the latitude and longitude of each grid, and used the API to obtain the travel time and travel distance between each grid. We chose "Minimize travel time between an origin and a destination" as our best-path algorithm option. We set the departure time at 08:00 to avoid the difference in return time results at different times of the day.

Step 4: Calculate job accessibility

Finally, we calculated job accessibility A_i^m by travel mode m:

$$A_i^{Tm} = \sum_{i\in\{d_{ij\leq}d_0\}} J_j^{Tm}\, f_t(t_{ij}) \tag{1}$$

Where A_i^m represents job accessibility of work type T by travel mode m at grid i; J_j^m is the number of jobs of type T that can be accessed by travel mode m at location j within the threshold travel time of i ($d_{ij\leq}d_0$); and $f^{tm}(t_{ij})$ is the decay function of travel time by travel mode m:

$$f^{tm}(t_{ij}) = e^{\beta^{tm} t_{ij}} \quad (2)$$

where β^{tm} is the decay coefficient by mode m and t_{ij} denotes travel time between location i and location j.

4.4 Estimation of spatial mismatch

To measure spatial mismatch between job accessibility and residential distribution, we calculated the difference between them in each grid unit. The formula is:

$$S_i^{tm} = \frac{P_i^t}{\sum_{i=1}^{n} P_i^T} - \frac{\sum_{i=1}^{n} P_i^t}{\sum_{i=1}^{n} P_i^T} * \frac{A_i^{Tm}}{\sum_{i=1}^{n} A_i^{Tm}} \quad (3)$$

Where S_i^{tm} refers to the difference between accessibility of type T jobs by travel mode m and residential distribution of type t workers at location i.

Unlike previous studies (e.g., Fan et al., 2014), the spatial mismatch measured by distinguishing different types of occupations and workers (i.e., blue-collar, pink-collar and white-collar) also incorporates competition between locals and migrants. In other words, the corresponding jobs must be allocated to the corresponding local workers and migrant workers in accordance with the ratio of local workers and migrant workers. P_i^T represents the sum of local and migrant workers of type T at location i and P_i^t represents the local or migrant workers of type T at location i.

4.4 Results

The method discussed in Sections 3.3 and 3.4 was used to identify the accessibility of different types of jobs and the degree of spatial mismatch for the corresponding workers. As mentioned, in our data, blue-, pink-, and white-collar jobs comprised 56%, 32%, and 12%, respectively, of the jobs, while blue-, pink, and white-collar workers comprised 16%, 31%, and 53%, respectively, of the workers. The inconsistency in the percentage of jobs and corresponding workers is caused by the difference in the statistical classification of industries and occupations (see Appendix I and II). In fact, a certain percentage of white-collar workers may be engaged in blue- or pink-collar jobs. For example, some white-collar workers are the person in charge or engineering technicians of a certain manufacturing industry. Therefore, we use total jobs instead of white-collar jobs when calculating the degree of spatial match for white-collar workers. The following subsections present a spatial mismatch assessment by groups.

4.4.1 Blue-collar workers’ residences and jobs

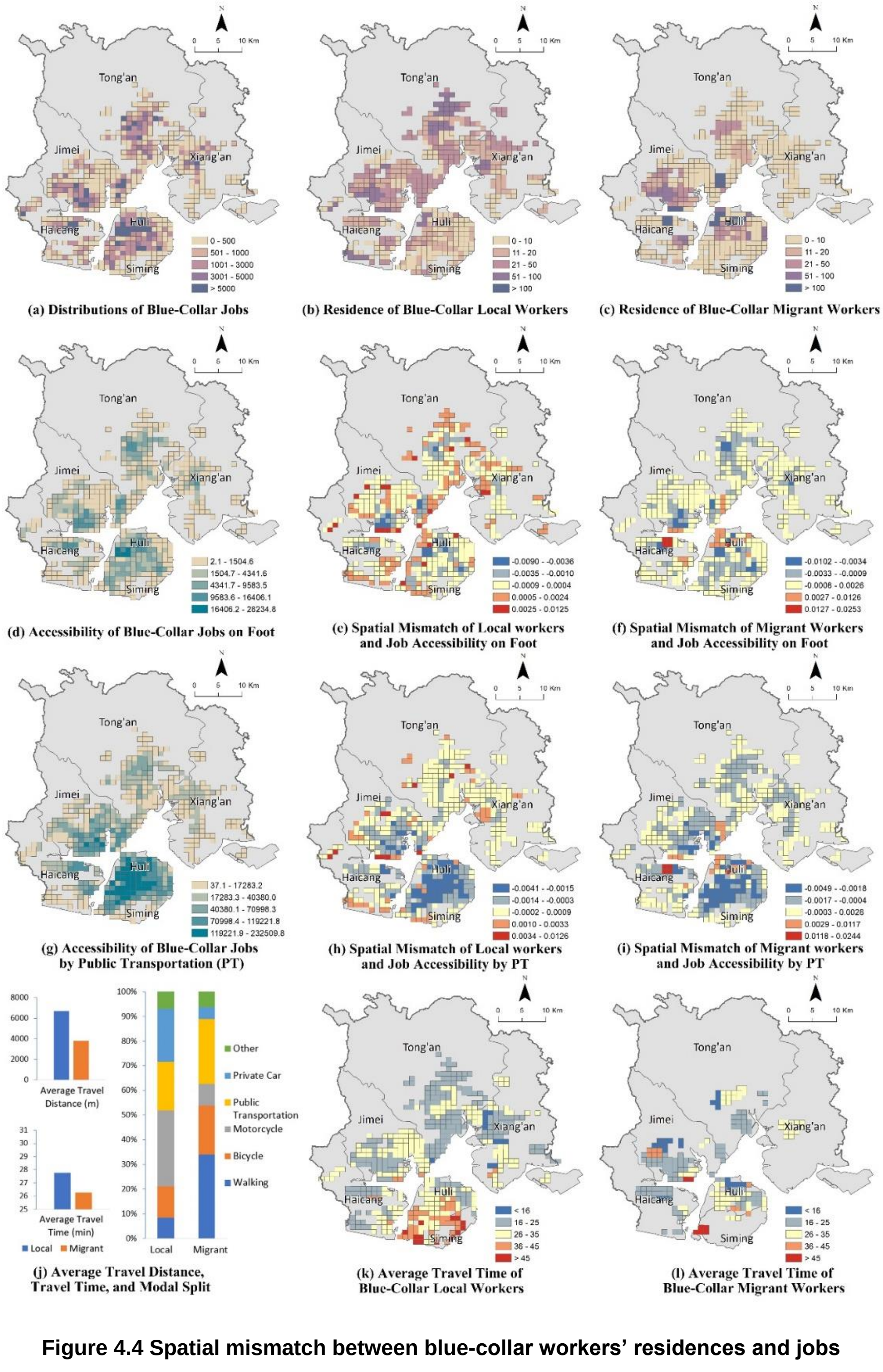


Figure 4.4 Spatial mismatch between blue-collar workers’ residences and jobs

With regard to the spatial distribution of residents, there is a considerable difference between blue-collar local workers (workers with Xiamen *hukous*) and blue-collar migrant workers (workers without Xiamen *hukous*). Concentrations of blue-collar local workers' homes can be found particularly in the outer districts, and especially on the urban fringe. In the recent past, these were farmers living in the villages on the urban fringe of Xiamen city. Many of them now work in the industrial or service sector, while still living in their original houses in the villages. In contrast, most blue-collar migrants live in urban villages, which are mostly located close to the industrial areas.

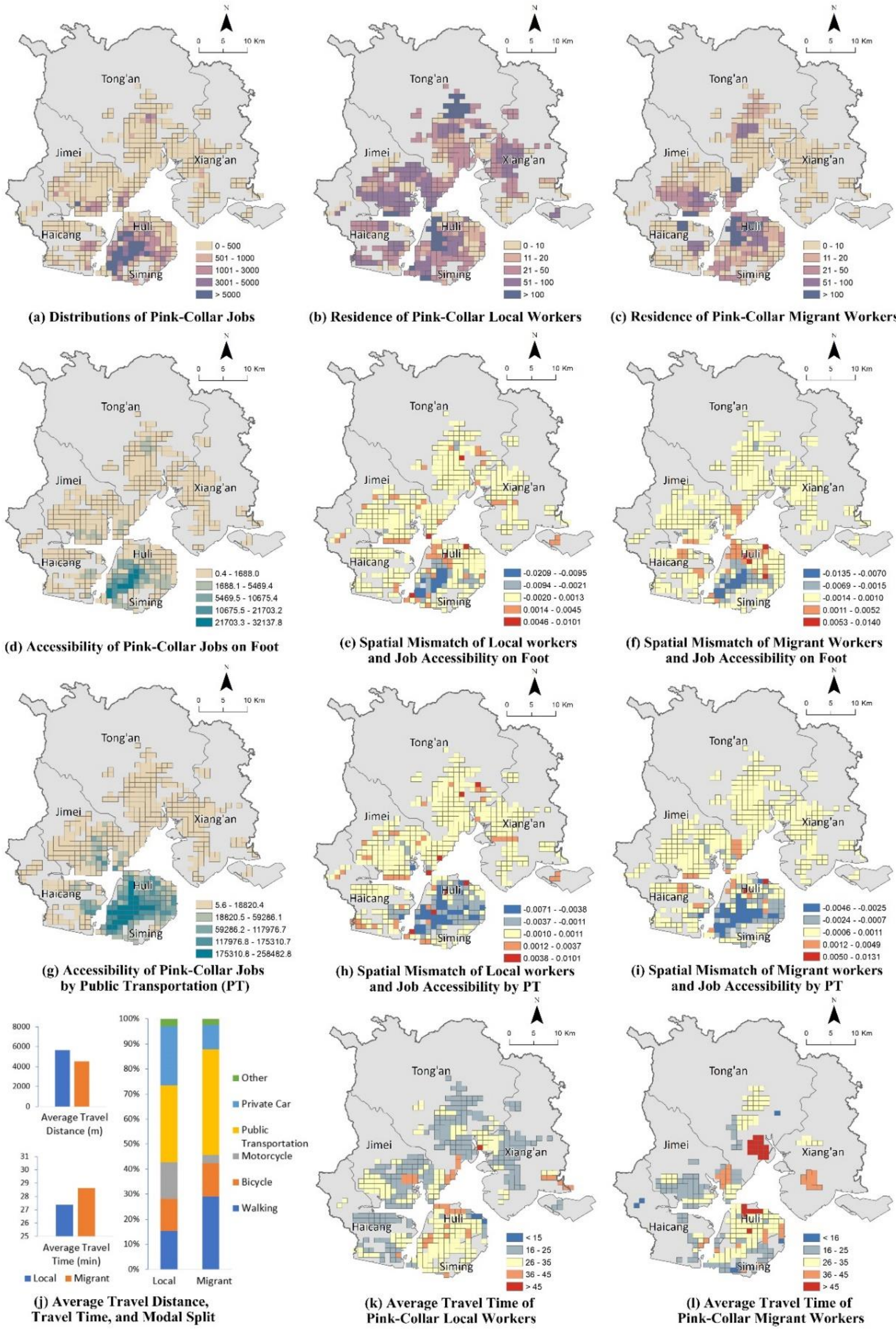
Regarding blue-collar jobs that can be reached on foot, the spatial pattern presents a polycentric structure with five centers: one in Huli district, where a tariff-free zone and high-tech industry are located; one in Haicang district, where heavy industry is located; two in Jimei district, where the Taiwanese investment zones are located; and one in Tong'an district, where heavy industry is located. These five centers are large industrial zones that were built following the transformation of Xiamen from an "island city" in the 1980s to an "island–gulf city" in the 1990s (Cao & Liu, 2007).

In terms of the spatial mismatch for local workers and migrant workers, in general, public transportation greatly improves employment accessibility. Correspondingly, the negative value (blue color) in Figures 4.4(h) and 4.4(i) (more jobs than workers) is greater than that in Figures 4.4(e) and 4.4(f), while the positive value (red color) in Figures 4.4(h) and 4.4(i) (more workers than jobs) is smaller than that in Figures 4.4(e) and 4(f). For blue-collar local workers, the spatial mismatch mainly occurs in the outer urban areas, partly on the southwest coast of Siming District. For blue-collar migrant workers, the spatial mismatch mainly occurs in Haicang, Huli, and Jimei, where migrant workers are the most concentrated. In general, the spatial mismatch for local workers is greater than that for migrant workers, which is also reflected in the fact that the average travel distance and travel time of the former are much longer than those of the latter.

In order to examine whether the spatial mismatch caused the longer travel time, we compared Figures 4.4(h) and 4.4(i) with Figures 4.4(k) and 4.4(l). It should be noted that when calculating the average travel time for each spatial unit, we only selected grids with a cumulative number of trips > 5 to avoid the extreme values caused by only one or two trips in some grids. In general, the grids in which job and worker distribution are reasonably balanced (the yellow parts in Figures 4.4(h) and 4.4(i)) tend to have the lowest average travel time (the blue parts in Figures 4.4(k) and 4.4(l)).

Contrary to our expectation, areas with more workers than jobs do not have increased travel times, and areas with far more jobs than workers do not have reduced travel times. In terms of local workers, although the peripheral areas have fewer jobs than workers, the average travel time is short, while in the inner urban areas where there are more jobs than workers, the average travel time is relatively long (Figure 4.4(k)). This is mainly caused by the difference in travel mode between residents in the inner districts and those in the outer districts. In the inner districts, public transportation is the main mode of commuting, with about 40% of blue-collar local workers commuting by public transportation, while only 10% of blue-collar local workers in the outer districts use public transportation. Instead, most of them use private cars or motorcycles to commute, thereby reducing their commuting time. As for migrant workers, the comparison between Figure 4.4(i) and Figure 4.4(l) shows that the average travel time in these sparsely populated areas is relatively long, while the average travel time is short in the areas where migrant workers are concentrated. In general, the average travel time is short in densely populated areas.

4.4.2 Pink-collar workers' residences and jobs



(a) Distributions of Pink-Collar Jobs
(b) Residence of Pink-Collar Local Workers
(c) Residence of Pink-Collar Migrant Workers
(d) Accessibility of Pink-Collar Jobs on Foot
(e) Spatial Mismatch of Local workers and Job Accessibility on Foot
(f) Spatial Mismatch of Migrant Workers and Job Accessibility on Foot
(g) Accessibility of Pink-Collar Jobs by Public Transportation (PT)
(h) Spatial Mismatch of Local workers and Job Accessibility by PT
(i) Spatial Mismatch of Migrant workers and Job Accessibility by PT
(j) Average Travel Distance, Travel Time, and Modal Split
(k) Average Travel Time of Pink-Collar Local Workers
(l) Average Travel Time of Pink-Collar Migrant Workers

Figure 4.5 Spatial mismatch between pink-collar workers' residences and jobs

Regarding the spatial distribution of residences, a considerable difference between pink-collar local workers and pink-collar migrant workers can be seen (Figures 5(b) and 5(c)). The residential spatial pattern of pink-collar locals is relatively more dispersed than that of pink-collar migrants. There are two main reasons for this. First, the farmers (locals) in the former villages on the urban fringe of the city switched to work in non-agricultural sectors, doing both blue-collar and pink-collar jobs. Second, also other low-educated locals across the city engage in pink-collar jobs because of their low-skill demands. In contrast, like blue-collar migrants, pink-collar migrants live primarily in urban villages, most of which are quite centrally located near employment concentrations.

With respect to the accessibility of pink-collar jobs on foot, a huge concentration can be found on Xiamen Island. This area is packed with tourist attractions and commercial sites, and both locals and tourists engage in business and leisure activities here. Accordingly, this centrally located area aggregates a range of jobs oriented toward personal services. With respect to the accessibility of pink-collar jobs by public transportation, most of Xiamen Island (Siming and Huli districts) is highly accessible, indicating that the efficient public transportation system on the island greatly improves the accessibility of this area.

For local pink-collar workers, spatial mismatch with fewer job opportunities than workers mainly occurs in some scattered areas. In comparison to blue-collar local workers, the spatial mismatch for pink-collar local workers is not as great, partly reflecting that the former's average travel distance (6700 m) is longer than the latter's (5600 m). For pink-collar migrant workers, similar to blue-collar migrants, the spatial mismatch mainly occurs in areas with a high concentration of migrant workers in Haicang, Huli, and Jimei. Compared to blue-collar migrant workers, the spatial mismatch for pink-collar migrant workers is slightly greater, which is partly reflected in the fact that the former's average travel distance (3800 m) is greater than the latter's (4500 m). Comparing local and migrant groups of pink-collar workers, we can see that the spatial mismatch for local workers is greater than that for migrant workers, which is also reflected in the fact that the former's average travel distance is longer than the latter's. Nevertheless, due to the differences in their travel modes, the average travel time of the former is shorter than that of the latter.

Since the proportion of public transportation trips is greater than that of walking trips for both local and migrant workers, we chose Figures 4.5(h) and 4.5(i) as the spatial mismatch for local and migrant workers, respectively. Accordingly, we compared those figures with Figures 4.5(k) and 4.5(l) to examine whether the spatial mismatch caused the longer travel time. Again, the grids with basically a balanced job–worker distribution tend to have the lowest average travel time. For both local and migrant workers, there is insufficient evidence that the spatial mismatch calculated by potential job accessibility causes an increase in actual commuting time. Those grids with a relatively long average travel time tend to be in areas with more jobs than workers or a balance between jobs and workers. However, a comparison between the distribution of workers (Figures 5(b) and

5(c)) with the average travel time distribution (Figures 5(k) and 5(l)) shows that the average travel time in relatively sparsely populated areas is longer. This result is consistent with the situation of blue-collar workers.

4.4.3 White-collar workers' residences and jobs

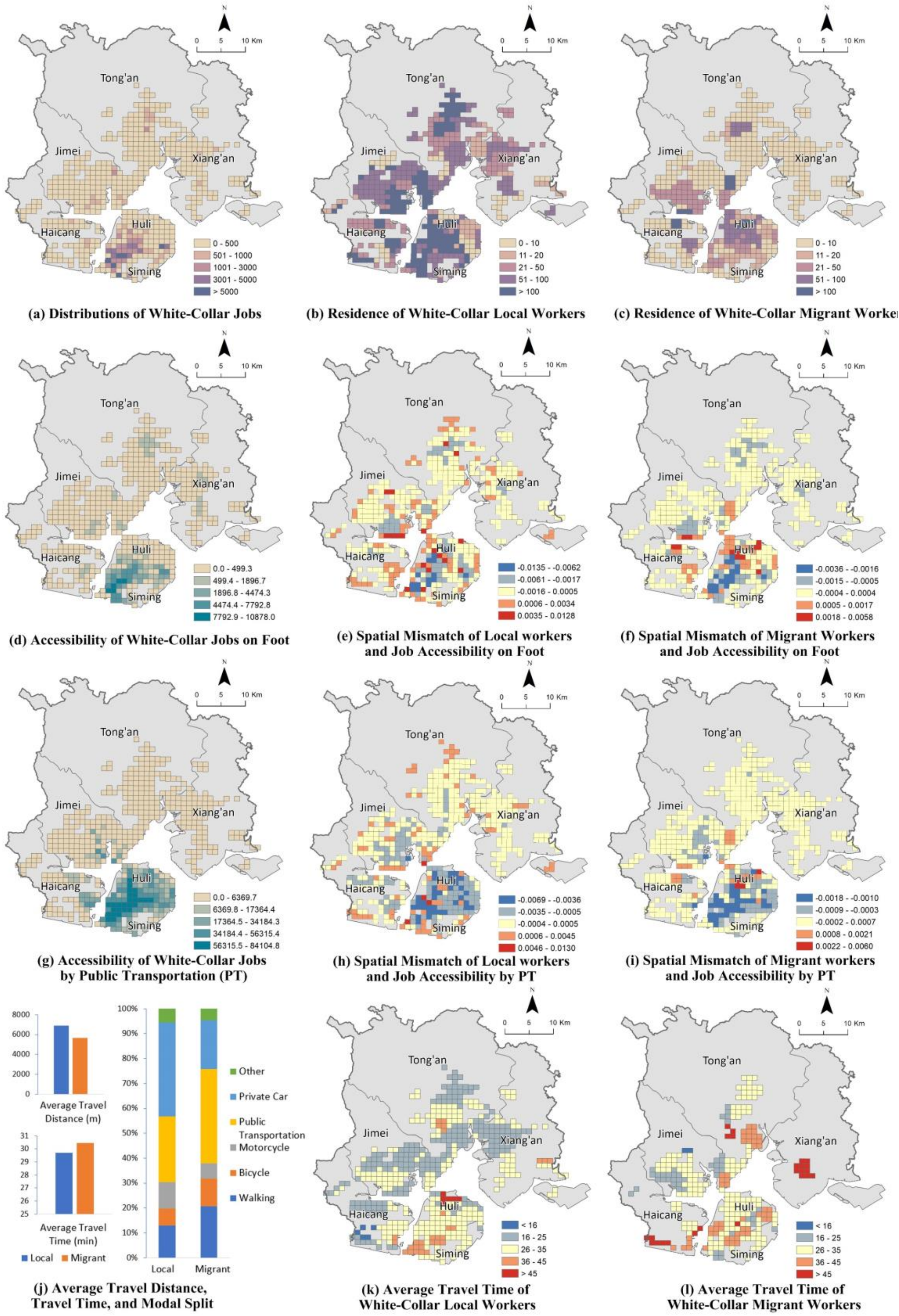


Figure 4.6 Spatial mismatch between white-collar workers' residences and jobs

Note: we use total jobs instead of white-collar jobs when calculating the degree of spatial match for white-collar workers (Figures 6(e), 6(f), 6(h), and 6(i)).

In terms of white-collar workers, we found that local workers and migrant workers differ substantially in their residential distribution (Figures 6(b) and 6(c)). White-collar locals reside relatively homogeneously across the city, while the homes of white-collar migrants are quite concentrated in certain places. Most white-collar migrants live in places that have been redeveloped or are located in newly built areas near the urban villages. Their distribution is similar to the distribution of blue-collar and pink-collar migrant workers. This result shows that migrant workers tend to agglomerate, mainly in a few specific areas.

With respect to the accessibility of white-collar jobs on foot, a huge concentration of such jobs can be found on Xiamen Island, where Xiamen's central business district is located. With respect to the accessibility of white-collar jobs by public transportation, these jobs are highly accessible from most areas of Xiamen Island (Siming and Huli districts), indicating that the efficient public transportation system on the island greatly improves the accessibility of these jobs.

For white-collar local workers, spatial mismatch with fewer job opportunities than workers mainly occurs in some scattered areas (Figures 4.6(h)). Compared with blue- and pink-collar local workers, the degree of spatial mismatch for white-collar local workers is the largest, reflected in the longest average travel distance (6900 m). For white-collar migrant workers, as for other types of migrants, the spatial mismatch mainly occurs in areas with a high concentration of migrant workers in the districts of Haicang, Huli, and Jimei. Compared with blue- and pink-collar migrant workers, the spatial mismatch for white-collar migrant workers is greater and the average travel distance is the longest (5700 m). Again, the spatial mismatch for local workers is greater than that for migrant workers. However, as in the case of pink-collar workers, the average travel time of the local workers is shorter than that of migrant workers due to differences in their travel modes.

Considering their preferred mode of travel, we compared Figures 4.6(h) and 4.6(i) with Figures 4.6(k) and 4.6(l) to examine whether the spatial mismatch caused longer travel times. The results show that grids with a balanced jobs–workers distribution tend to have the lowest average commuting time. We found that inner districts, where the number of available jobs vastly outnumbered the population, were areas with longer average commutes. This is mainly because the high density of the inner city can support a denser bus network and a higher bus frequency, and therefore people in the inner city are more inclined to use public transportation for commuting, which leads to longer commuting times. Consistent with the results for blue- and pink-collar migrant workers, areas where white-collar migrant workers have a longer average commuting time tend to be relatively sparsely populated. On the contrary, the average commuting time in places where migrant workers are concentrated is relatively short, confirming the existence of the enclave effect ("acquaintance society")—an effect that has its roots in social networks, which ensure that individuals find jobs in nearby communities through referrals from relatives, friends, and home-towners (Bi et al., 2019).

4.5 Conclusions and discussion

The present research took Xiamen city in China as a case study to analyze the degree of spatial mismatch for different socioeconomic groups. It contributes to previous research by differentiating between groups of workers according to socioeconomic status and *hukou* status.

We optimized the dissimilarity index to identify spatial differences within the city. This resulted in three major findings:

- Blue-collar, pink-collar, and white-collar workers, who are further categorized as either locals or migrants, experience varying degrees of job accessibility and spatial mismatch. In general, the degree of spatial mismatch is greater for blue-collar and pink-collar locals than it is for blue-collar and pink-collar migrants. Most blue-collar locals live outside Xiamen Island, in particular on the urban fringe. The main reason for this is their background as farmers and the high prices of apartments on the island. The spatial residential pattern of pink-collar locals is relatively dispersed. In contrast, both blue-collar and pink-collar migrant workers tend to rent rooms or apartments in one of the urban villages. They are thus much more flexible than local homeowners and can easily adjust where they live to changes in where they work. Moreover, most of the urban villages encompass or are located near industrial or central-service areas. In other words, most blue-collar and pink-collar migrants live close to where they work. As a result, the spatial mismatch for both blue-collar and pink-collar migrants is much less than it is for blue-collar and pink-collar locals. For white-collar jobs and workers, there are differences in residential distribution between locals (whose homes are more evenly dispersed) and migrants (whose homes are more concentrated), while their access to white-collar jobs is differential, with high values on the island. Furthermore, white-collar local workers suffer greater spatial mismatch than white-collar migrant workers.
- Despite the greater spatial mismatch, the commuting time of local workers (especially pink- and white-collar workers) is shorter than that of their migrant counterparts. This is due to the difference in transportation modes between local and migrant workers. In general, local workers use private cars or motorbikes more often than migrant workers, which can to a certain extent reduce their travel time. Thus, although migrant workers have advantages over local workers in terms of the spatial relationship between employment and residence, they have disadvantages in terms of travel time due to travel mode.
- The proportion of public transportation in the modal split in areas with higher employment (inner districts) is much greater than in outer districts. Although this increases the average travel time in these areas to some degree, people find it acceptable. For example, the average commuting time in the inner districts is longer than that in the outer districts, despite a much larger concentration of jobs there (especially pink-collar and white-collar jobs), because the main mode of motorized

travel in the area is public transportation. Still, for white-collar and pink-collar workers the average commuting time in the inner districts is less than 45 minutes (except for the airport area, in the northeast), which is within people's tolerance (Huang et al., 2018). In addition, areas with a longer average commuting time tend to be relatively sparsely populated. This result is particularly pronounced among migrant workers, indicating that concentrations of migrant workers in China have an enclave effect, which can reduce the commuting time to some extent. The enclave effect is derived from the "acquaintance society," which finds jobs in the nearest neighborhood through referrals from relatives, friends, and home-towners (Bi et al., 2019).

The findings of this research have important policy implications concerning disadvantaged groups, including blue-collar and pink-collar workers, both locals and migrants:

- This research provides a helpful reference for the locational choice of affordable housing. With the increasingly limited supply of land on Xiamen Island, government-subsidized affordable housing—which is mainly targeted at low-income local residents—has primarily been built outside Xiamen Island. Given that most pink-collar jobs are located on Xiamen Island, this exacerbates the spatial mismatch for its residents. Affordable housing should preferably be built in areas close to these pink-collar jobs, or in areas with efficient public transportation. Suitable places include the areas around the metro stations that are being planned or are under construction, including those outside Xiamen Island but with fast connections to it.
- A large number of urban villages in Xiamen, particularly those on the island, have been or will soon be demolished as a result of the political and economic drivers for continuing redevelopment. If these demolitions continue, migrants in Xiamen will be forced to move to low-rent housing in outer urban areas, or even to other cities. The disposable income of Xiamen residents is less than that of residents of larger eastern coastal cities, such as Nanjing and Ningbo, while their consumption expenditure (especially housing expenditure) is greater, meaning that Xiamen is less attractive than the other two cities (Nanjing Municipal Bureau of Statistics, 2020; Ningbo Municipal Bureau of Statistics, 2020; Xiamen Municipal Bureau of Statistics, 2020). If Xiamen is unable to provide a large amount of low-rent housing, it may face a large migrant exodus. Therefore, the government should consider increasing the provision of and access to government-subsidized housing so that the migrant population can also enjoy preferential policies such as low-rent housing. Again, this low-rent housing should be built around metro stations to improve migrants' access to jobs, or provide public rental housing in combination with the incremental upgrading of urban villages.
- Last, but not least, a certain proportion of jobs—especially pink-collar jobs—should be distributed in the new outer city areas. If the number of people living in the outer districts increases while the number of jobs there does not, in the future

there will be an increase in commuting flows between the inner district and the outer districts, which will put tremendous pressure on the bridges and tunnels connecting the inner and outer districts. These newly created jobs should also be situated close to metro stations to slowly reduce the dependence on cars and motorcycles in the outer districts.

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5. Do migrants and locals differ in commuting behavior? A case study of Xiamen, China

This chapter is based on the article: Li, Y., Geertman, S., Hooimeijer, P., Lin, Y., & Yang, H. (2021). Do migrants and locals differ in commuting behavior? A case study of Xiamen, China. Transport Policy, 108, 1-10.

ABSTRACT

Although there is a growing body of literature on the commuting pattern of rural migrants in China, few studies have examined the diversity in commuting behavior among workers with different occupations. The present research used the 2015 Xiamen household travel survey to examine commuting distances and commuting times of distinctive types of workers in the city. The results reveal differences in commuting behaviors among distinctive socioeconomic groups, namely blue-collar, pink-collar, or white-collar local or migrant workers. For local residents, blue-collar workers have the longest commute distance, while pink-collar workers have the shortest commute distance. Migrant workers—for both blue-collar and pink-collar—in general commute over shorter distances than local workers to reach their workplaces. However, planning practices have attempted to demolish their affordable rental housing in urban villages, which will increase their commuting times and costs and exacerbate sociospatial inequality. These findings can be of practical use when offering alternative housing for migrants in urban redevelopment.

Keywords: commuting bahaviors, spatial mismatch, different socioeconomic groups, migrants, China

5.1 Introduction

Since Kain (1968) presented the spatial mismatch hypothesis in his article, in which he argued that employment discrimination, suburbanization of employment, and residential segregation resulted in high levels of the unemployment rate for African Americans, it has been the subject of extensive research (Bi et al., 2019; Brandtner et al., 2019; Theys et al., 2019). The spatial mismatch among African Americans is due to the large-scale separation of workplaces and housings, which is caused by the continued suburbanization of manufacturing and the concentration of African Americans in downtown areas.

This research suggests that spatial mismatch is related to the spatial distribution of different industries on the one hand, and the residential distribution of corresponding workers on the other hand. In this regard, China and the United States have both similarities and differences. In the past few decades, many Chinese cities have experienced rapid urbanization and socio-spatial transformation. As in the United States, manufacturing jobs in inner cities have been moved out to the suburbs and replaced by high-level jobs such as finance and business services (Liu et al., 2017; Michaels et al., 2019). However, there are differences between the two countries in terms of residential distributions. Blue-collar workers in the United States generally live in inner cities, while blue-collar workers in China generally live in inner suburbs because they cannot afford the high housing prices in inner cities (Fan et al., 2014). Given this difference, will China's blue-collar workers also have a spatial mismatch like the US? After the blue-collar jobs in the inner city are replaced by pink-collar or white-collar jobs, is there a spatial mismatch between pink-collar workers and white-collar workers? None of these research questions has been answered by previous research.

In terms of residential distribution, one factor of particular concern is residential segregation. In the case of the United States, this is reflected in the residential segregation of African Americans in the inner city. In the case of China, residential segregation mainly occurs among migrants living in urban villages. To explain this phenomenon, one has to explain China's household registration system. China's rapid economic reforms and urbanization in recent decades have prompted large-scale rural population migration, which has caused a certain degree of residential segregation in urban areas. Since the majority of rural migrants lack urban citizenship (*hukou*) and have involved in low-income jobs, most of them have limited access to commercial and affordable housing in the city. As a consequence, they have concentrated in "villages in the city" (ViC) or urban villages that provide rental housing for them (Lin et al., 2011). Urban villages were previously rural settlements but were later swallowed by urban development. Local governments often requisition farmland in rural areas because the requisition of residential areas requires higher compensation levels. As a result, the original houses that were retained were rebuilt by the villagers and rented to rural migrants. Previous studies show that urban villages are often close to the working place of migrants and have good access to public transportation (Lin et al., 2011), and there is heterogeneity among migrant groups (Liu et al., 2018). Nevertheless, their studies are mainly based on qualitative research or specific case studies. Not all rural migrants settle in urban villages, many of them live in factory dormitories and other urban neighborhoods (especially high-skilled migrants). An important factor to be considered is that many old cities are facing urban renewal and a large number of urban villages in inner cities are facing demolition. Therefore, it is necessary to understand the role of urban villages in spatial coordination of job-housing relationships in order to effectively manage job-housing relationships of displaced residents and to provide effective transport policies. Besides rural migrants, there are various types of local residents, who have been involved in different kinds of jobs and lived in different parts of the city. In general, the spatial relationship between the residences and jobs of different socioeconomic groups remains unclear. Exploring this mechanism can not only explain the consistency and differences of spatial mismatch in different countries but also provide policy recommendations for urban planning and transportation.

Therefore, this research fills the mentioned gaps. It investigates the spatial relationship between residences and jobs and the commuting patterns among different socioeconomic groups. It takes Xiamen city as an example. The labor workers, both locals and migrants, are divided into three categories, namely blue-collar workers, pink-collar workers, and white-collar workers. Blue-collar workers perform skilled or unskilled manual labor; pink-collar workers perform service-oriented work, such as customer interaction and sales; and white-collar workers work in an office environment. Compared to white-collar workers, blue-collar and pink-collar workers have lower wages and lower education levels (Fan et al., 2014). This classification method is mainly used because they have certain characteristics in spatial distribution, and therefore it can better explain the influence mechanism. To understand the similarities and differences between the commuting patterns of these workers, we applied a linear regression model to identify and explain differences in commuting time and commuting distance.

The paper is structured as follows. Section 2 presents a review of the literature on the spatial mismatch and its relationship to commuting behavior. Section 3 describes the data sources and the dependent and independent variables. Section 4 analyses spatial patterns of locals and migrants. Section 5 presents the results of the regression models on commuting patterns. And section 5 provides some conclusions and further discussions.

5.2 Literature review

Since Kain (1968) proposed the concept of spatial mismatch, many studies have been conducted to measure the degree of spatial mismatch and its impact on employment outcome. In general, the degree of spatial mismatch is often measured by dissimilarity index (Easley, 2018), commuting distance (Blumenberg & Manville, 2004), and commuting time (Bi et al., 2019). The dissimilarity index measures the evenness of different groups in all communities within a city or metropolitan area, which reflects the degree of spatial mismatch within the urban space rather than at the individual level. At the micro level, commuting time and commuting distance are more appropriate indicators to reflect the degree of spatial mismatch (Bi et al., 2019). In general, spatial mismatch is caused by different individuals' choice of residence and work location (Figure 5.1). Affected by socioeconomic attributes, there is an inconsistency between individual housing and job choices, which will lead to differences in the degree of their spatial mismatch.

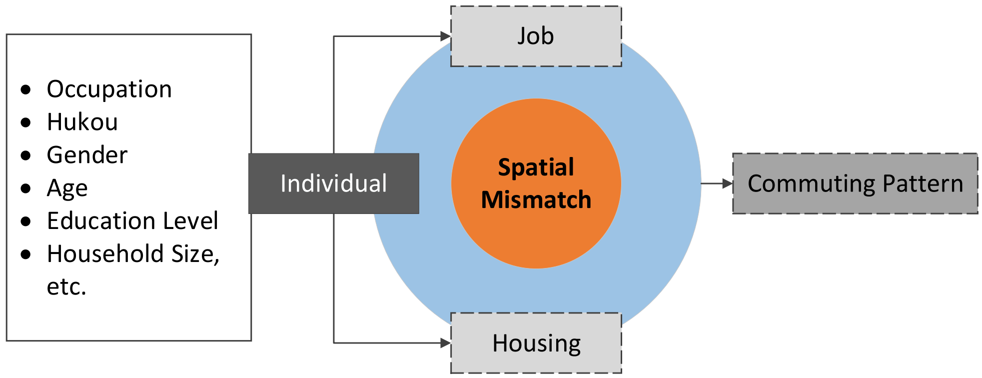

Figure 5.1 The Mechanisms of Spatial Mismatch

Occupation is a noteworthy influence factor, as spatial mismatch is caused by the inconsistent spatial distribution of certain industries and workers (Zhou et al., 2018). Cities in many countries around the world have experienced a decline in blue-collar jobs in the inner cities and have been substituted by higher value-added white-collar jobs. However, the spatial distribution of corresponding workers varies among countries. For instance, blue-collar African Americans in the United States generally tend to live in the inner city, while blue-collar workers in China generally live in the inner suburbs (Fan et al., 2014). Although these differences may lead to different spatial organization and travel patterns, few studies in China have examined the spatial distribution of different industries and corresponding workers. Studies by Fan et al. (2014) are an exception. They found that in Beijing, spatial mismatch among blue-collar workers is greater than among pink-collar workers. They also found that migrant workers experience greater spatial mismatch than local workers, which is exactly the opposite of what happens in other cities (Li & Liu, 2016). However, they use a dissimilarity index, which focuses on the spatial separation and agglomeration of different groups, rather than the ease of access to the workplace at the individual level.

An equally important perspective on spatial mismatch in China is the degree of residential segregation of migrant populations caused by *hukou*. In the united states, a large body of research shows that ethnic groups experience longer commuting distances and time than white people. For instance, Kain (1968) presented the spatial mismatch hypothesis that suburbanized jobs and limited transportation options resulted in long-distance commuting and poor employment outcomes among inner-city African Americans. Unlike the United States, race issues are not very significant in China (Fan et al., 2014). But a big challenge in the Chinese context is the residential segregation caused by the *hukou* system. This system, which was instituted in the 1950s, is a family registration program that regulates population distribution and rural-to-urban migration. It also excludes migrants from several social services (including subsidized housing) in an attempt to restrict the massive influx of rural migrants to the cities. Due to their lack of urban citizenship (*hukou*) and financial means, most rural migrants have limited access to commercial and/or affordable housing in the city. As a consequence, most of these migrants rent rooms in villagers' homes in urban villages, because the rents are much cheaper than in other places and urban villages are often situated close to the main industrial workplaces. With respect to commuting distance and time, extensive research has shown that migrants tend to have more balanced job-housing relationships than local *hukou* residents, leading to a shorter commuting time and distance (Li & Liu, 2017; Li & Liu, 2016; Zhang et al., 2018). However, differences exist between diverse migrants in terms of commuting behavior. Zhang et al. (2018) found that higher-skilled migrants commute over longer distances than lower-skilled migrants and concluded that institutional barriers that restrict mobility in the labor market led to longer commute distances for higher-skilled migrants.

In addition to *hukou* and occupation type, commuting time and commuting distance are also affected by other factors. These factors include spatial structure and socioeconomic factors. A large body of literature has examined the relationship between spatial structure and commuting patterns. For instance, Huang et al. (2020) found that a mixed land-use pattern led to a shorter average time/distance. Neighborhood and street characteristics, such as dense road network and high transit accessibility help to decrease commuting distance (Huang et al., 2018). Zhang *et al.* (2012) found that residential density and employment density had a negative on vehicle miles traveled. Another aspect of the spatial attribute is regional differences. Van Ham and Hooimeijer (2009) observed that the average commuting time in the intermediate zone was higher than that of the periphery.

In addition to the spatial structure factors, socioeconomic factors play an important role in determining commuting behavior. Existing studies have found that women commute shorter distances than men (Cassel et al., 2013; Hu et al., 2018; Zhu et al., 2017). This result is explained by the fact that women take a larger share of childcare and unpaid housework, leaving less time for commuting (Johnston-Anumonwo, 1992; Turner & Niemeier, 1997). Several lines of evidence suggest that age is negatively related to trip distance (Mercado & Páez, 2009). Education level also influences commuting patterns. People with a higher level of education commute longer than those with a lower level of education (Zhu *et al.*, 2017; Hu *et al.*, 2018). Previous studies have explored the relationships between household attributes and commuting patterns. Mercado and Páez (2009) found that household size had a negative effect on commuting distance. A common finding is that renters have shorter commuting time and distances compare to homeowners (Helderman et al., 2004; Hu et al., 2018). Homeowners are much less likely to move than renters are, "as being a homeowner requires a substantial long-term financial commitment" (Dieleman, 2001; Helderman et al., 2004). As renters are higher in flexibility and residential mobility they are more likely to choose a residential location nearby the workplace. Therefore, these spatial structure factors and socioeconomic attribute factors were selected as control variables to be added to our model.

5.3 Methodology

5.3.1 Study area and data source

Xiamen is a sub-provincial city in Fujian province. It consists of Xiamen Island (which embraces the districts of Siming and Huli) and the mainland districts of Haicang, Jimei, Xiang'an, and Tong'an. The land area covers just under 1700 km^2 and the sea area over 390 km^2. In 2017, the permanent resident population of Xiamen reached 4 million, of whom 2.31 million were registered permanent residents. Among the registered population, the urban population amounted to 1.97 million people, of whom 55.8% (1.1 million) were living in Xiamen Island. Over time, the urbanized area has spread from Xiamen Island to the other districts on the mainland.

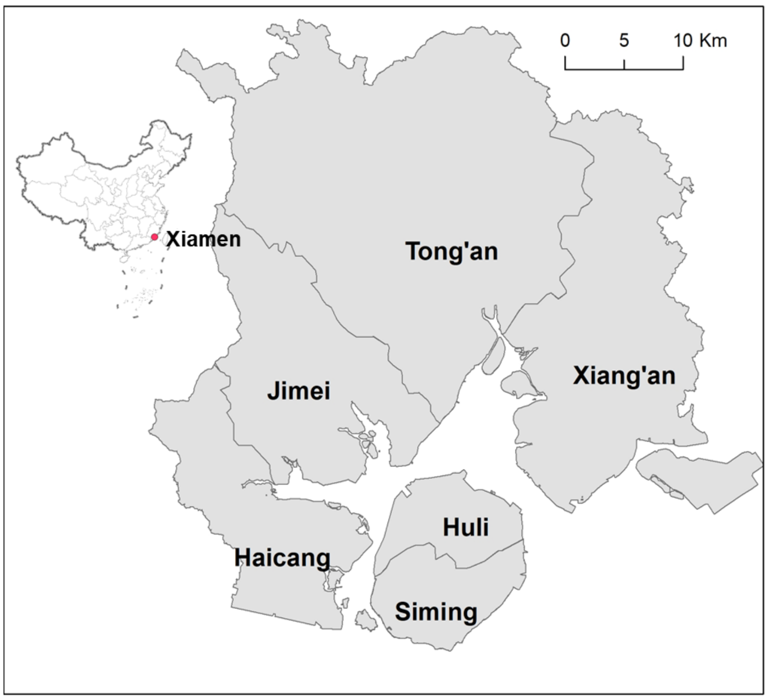

Figure 5.2 Xiamen city in China: location and administrative divisions

The analysis presented in this paper is based on data from the 2015 Xiamen household travel survey, covering 6 districts, 41 streets (towns), and 359 neighborhood committees (villages), with a sampling rate of 3%. The sample of this survey was based on the overall population distribution, household size, gender structure, and age structure of the 2010 census data of Xiamen City. The survey was conducted from June 13 to 19, 2015. The investigator interviewed all members (aged 6 and above) of the surveyed families—which included representatives of both the registered population and the temporary resident population (migrants)—concerning their daily (24-hour) travel behavior. The original datasets contain 219, 552 travel data and 49, 531 commuting data, from which we selected the commuting data of blue-, pink-, and white-collar workers and deleted the missing and extreme values, resulting in 34,372 commuting data for the final dataset. The household data include address, traffic analysis zone (TAZ), household size, car ownership, housing area, home ownership, and so on. The individual data include personal information such as age, gender, *hukou* status, occupation, and education level. And the travel data include departure time, arrival time, departure location, arrival location, and travel mode.

5.3.2 Variables and methods

Consistent with previous studies, we performed multivariate regression analysis to explore the relationships between individual/spatial structure variables and commuting time/distance (Jain et al., 2018; Zhao et al., 2011).

Commuting time is the arrival time minus the departure time. As the household travel survey only provides departure TAZ and arrival TAZ, rather than actual commuting distance, we computed approximate values. To do so, we first used ArcGIS to compute the centroid of each TAZ. We then calculated commuting distance with the help of the Origin-Destination (OD) cost matrix analysis in ArcGIS. The OD distance ranges from 855 m to 49,953 m. If the departure TAZ and the arrival TAZ are the same, the OD distance equals 0. Since a value of 0 is not realistic, those valued 0 were assigned a new value, based on the speed of each commuting mode. The new value was obtained according to the following formula:

$$\mathrm{D}_i=\begin{cases}\mathrm{D}_i^{\prime} & \text{if } \mathrm{D}_i^{\prime} > 0\\ \mathrm{T}_i * \mathrm{S}_j^{*} & \text{if } \mathrm{D}_i^{\prime} = 0\end{cases} \tag{1}$$

Where D_i represents the new commuting distance of the *i*th commuting record; $\mathrm{D}_i^{\prime}$ represents the commuting distance of the *i*th commuting record computed by ArcGIS; T_i represents the commuting time of the *i*th commuting record;S_j^{*} is the average commuting speed of mode *j*. The modes include walking, cycling, bus, bus rapid transit (BRT), motorcycle, and private car.

$\mathrm{S}_j^{*}$was calculated based on the following formula:

$$S^{*} = \frac{\mathrm{D}_j^{*}}{\mathrm{T}_j^{*}} \tag{2}$$

Where D_j^{*} is the mean commuting distance of mode *j* for $\mathrm{D}_i^{\prime}$ greater 0; T_j^{*} is the mean commuting time of mode *j* for $\mathrm{D}_i^{\prime}$ greater 0.

When measuring job accessibility, we defined 60 minutes as the threshold time for public transportation and 30 minutes for walking, which account for 85% of all commutes on foot. We then counted the number of jobs that were accessible via that mode of transportation within that commuting time. As the average size of a TAZ in Xiamen is 9.2 km^2, which is too big to be able to produce accurate results, we used 100*100 m^2 as the basic spatial unit in our analysis and computed average values for each TAZ. Bus stop density is the total number of bus stops within each TAZ divided by the area of that TAZ (sq. km). Road density for each TAZ is the total road length (km) divided by the area of that TAZ (sq. km). We also examined the spatial structure variables of areas in Xiamen, namely Xiamen Island (including Siming and Huli districts) and the mainland districts (Haicang, Jimei, Xiang'an, and Tong'an). The socioeconomic variables were *hukou* status, gender, age, education level, household size, and home ownership.

In line with previous studies (Sandow & Westin, 2010; Zhang et al., 2012; Hu et al., 2018), we tested age square in our preliminary analysis. However, it was found that this variable had no effect on the dependent variable, so it was deleted. In our final models, the variance inflation factor (VIF) is less than 5, so the multicollinearity issue is not present.

5.3.3 Descriptive statistics

The distribution of individual and spatial factors, commuting distance, and commuting time has a distinct pattern per *hukou* type (Table 5.1).

Table 5.1 Descriptive statistics on worker types of migrants and local workers

	Locals	Migrant	Total
	Mean/percentage	Mean/percentage	Mean/percentage
Job accessibility by public transportation (unit: 10,000)	43.41	50.16	45.57
Job accessibility by walking (unit: 10,000)	7.21	7.64	7.34
Living in Xiamen Island			
Yes	54.2%	66.9%	58.3%
No	45.8%	33.1%	41.7%
Population density (unit: 10,000 per sq. km)	1.73	2.41	1.95
Job density (unit: 10,000 per sq. km)	0.90	1.09	0.96
Bus stop density (per sq. km)	6.12	6.29	6.17
Road density (per sq. km)	12.88	13.93	13.21
Gender			
Male	55.4%	57.8%	56.2%
Female	44.6%	42.2%	43.8%
Age	37.06	33.10	35.79
Education level			
Without college degree	69.2%	87.5%	75.1%
College degree	28.3%	12.0%	23.1%
Master or above	2.4%	0.5%	1.8%
Household size	3.29	2.54	3.05
Home ownership			
Owner	90.5%	13.9%	65.9%
Renter	9.5%	86.1%	34.1%

Occupation			
Blue-collar worker	10.9%	26.5%	15.9%
Pink-collar worker	27.8%	38.4%	31.2%
White-collar worker	61.4%	35.1%	52.9%
Living in urban village			
Yes	9.9%	35.6%	18.2%
No	90.1%	64.4%	81.8%

Note: Migrants refer to the population with non-local *hukou*.

With respect to the spatial factors, migrants in comparison to locals enjoy higher job accessibility by both public transportation and walking, are more likely to reside in Xiamen Island, and live in areas with higher population density, job density, bus stop density, and road density. As expected, migrants are more likely to live in urban villages (35.6%) than locals are (9.9%). These results are in accord with other recent studies indicating that migrants are more likely to rent housings in urban villages (Lin et al., 2014, 2017; Liu et al., 2017).

Regarding the socioeconomic factors, migrants in comparison to locals are, on average, younger, have a lower level of education, and live in smaller households. As expected, migrants are much less likely to be homeowners than locals. Only 13.9% of migrants are homeowners, while 90.5% of locals are homeowners. Migrants also differ from locals regarding their occupation. More than half of locals (61.4%) are white-collar workers, while just 35.1% of migrants are white-collar workers. Only 10.9% of locals are blue-collar workers, while 26.5% of migrants are blue-collar workers. And with regard to pink-collar workers, 27.8% of the migrants and 38.4% of the locals belong to this group.

Our two-sample t-test shows a significant difference between migrants and locals in commuting distance, while there is no significant difference in commuting time (Table 5.2).

Table 5.2 Two-sample two-tailed *t*-test of commuting distance and time

	Locals	Migrant	t	Df	Sig. (2-tailed)
Commuting distance (m)	6870.43	5307.01	-23.32	26713	0.00
Commuting time (min)	28.13	28.27	0.59	21288	0.56

On average, locals commute over longer distances (6.8 km) than migrants (5.3 km). The t-test shows that, on average, the spatial mismatch among locals is higher than that among migrants. Nevertheless, in terms of commuting time, no significant difference exists between locals and migrants (both have a commuting time of about 28 minutes).

As shown in Table 5.3, this result may be explained by the fact that locals are more likely than migrants to commute by 'faster' modes of transportation like motorcycles (15.2% vs 5.9%) or private cars (35.2% vs 12.2%).

Table 5.3 Commuting modes and *hukou* status

	Locals	Migrants	Total
Walking	14.4%	28.7%	18.6%
Cycling	10.1%	15.1%	11.4%
Bus	26.8%	35.5%	28.8%
BRT	2.8%	2.6%	2.7%
Motorcycle	15.2%	5.9%	11.8%
Private car	35.2%	12.2%	26.8%

5.4 Spatial Analysis

5.4.1 Distribution of local and migrant workers

The spatial distribution of workers by occupation is displayed in Figure 5.3. In general, local workers are relatively uniformly distributed throughout the city. In contrast, migrants are clustered in several specific areas regardless of their occupation type, including the northeast of Huli District, the northeast of Haicang District, and the east coast of Jimei District, which are all around industrial zones.

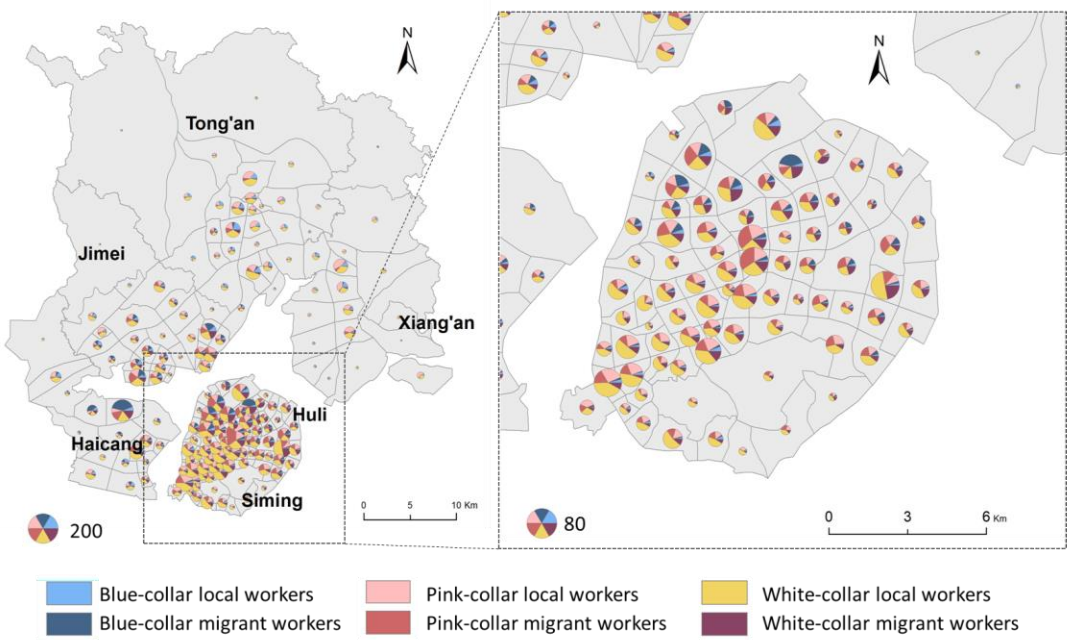

Figure 5.3 Distribution of workers by occupation

Note: We only consider three types of occupations, so some areas have no population. For example, there are a certain number of farmers in the periphery of the city, but the map shows no population.

Only a small portion of blue-collar local workers are distributed on Xiamen Island, and they are mainly living in the mainland districts, especially in Tong'an and Xiang'an districts. In terms of blue-collar migrants, most of their living locations are distributed in Haicang District, and some are distributed in Jimei District and Huli District, in which they are situated all around the industrial zones. The living places of pink- and white-collar local workers are relatively uniformly distributed throughout the city, while the distribution of pink- and white-collar migrant workers is similar to that of blue-collar migrant workers, mainly distributed in Haicang, Jimei, and Huli District. The dormitory buildings in the industrial zones and the low-cost housing rents in the surrounding urban villages attract a large number of migrants living concentrated around the industrial zones.

5.4.2 Commuting pattern

The overall commuting pattern of workers by occupation is shown in Figure 5.4. Obviously, the commuting behaviors of different groups are highly correlated with their distribution characteristics. For blue-collar local workers, since the living places of most of them are located in the mainland districts, large-volume commuting flows (larger than 6) mainly occur in these areas, and these large commuting flows are mainly in short distances. For blue-collar migrant workers, a lot of commuting flows occur within the TAZ. In addition, short-distance and large-volume commuting flow take place in Huli, Jimei, and Haicang districts where many industrial areas are clustered.

With respect to pink-collar local workers, the spatial coverage of their commuting flows is wider than that of blue-collar local workers. In terms of large-volume commuting flows, these appear in all six districts, mainly over short distances, and without mainland-island commuting. For pink-collar migrant workers, much of the commuting flows occur within the TAZ, but their spatial distribution is not as concentrated as with blue-collar migrant workers. In addition, short-distance and large-volume commuting flows are mainly generated in Xiamen Island, with a small amount occurring in Jimei and Haicai districts.

With respect to white-collar local workers, the spatial coverage of their commuting flows is the most extensive. Compared with the locals of the other two occupation groups, the commuting flows of the white-collar local workers within TAZ is relatively large, besides large-volume commuting flows between the TAZ, some of which are long-distance or even mainland-island commuting. For white-collar migrant workers, part of the commuting flows occurs within TAZ, and their spatial distribution is very similar to that of pink-collar migrants. Moreover, short-distance and large-volume commuting flows are mainly generated in Xiamen Island, with a small amount occurring in Jimei and Haicai districts.

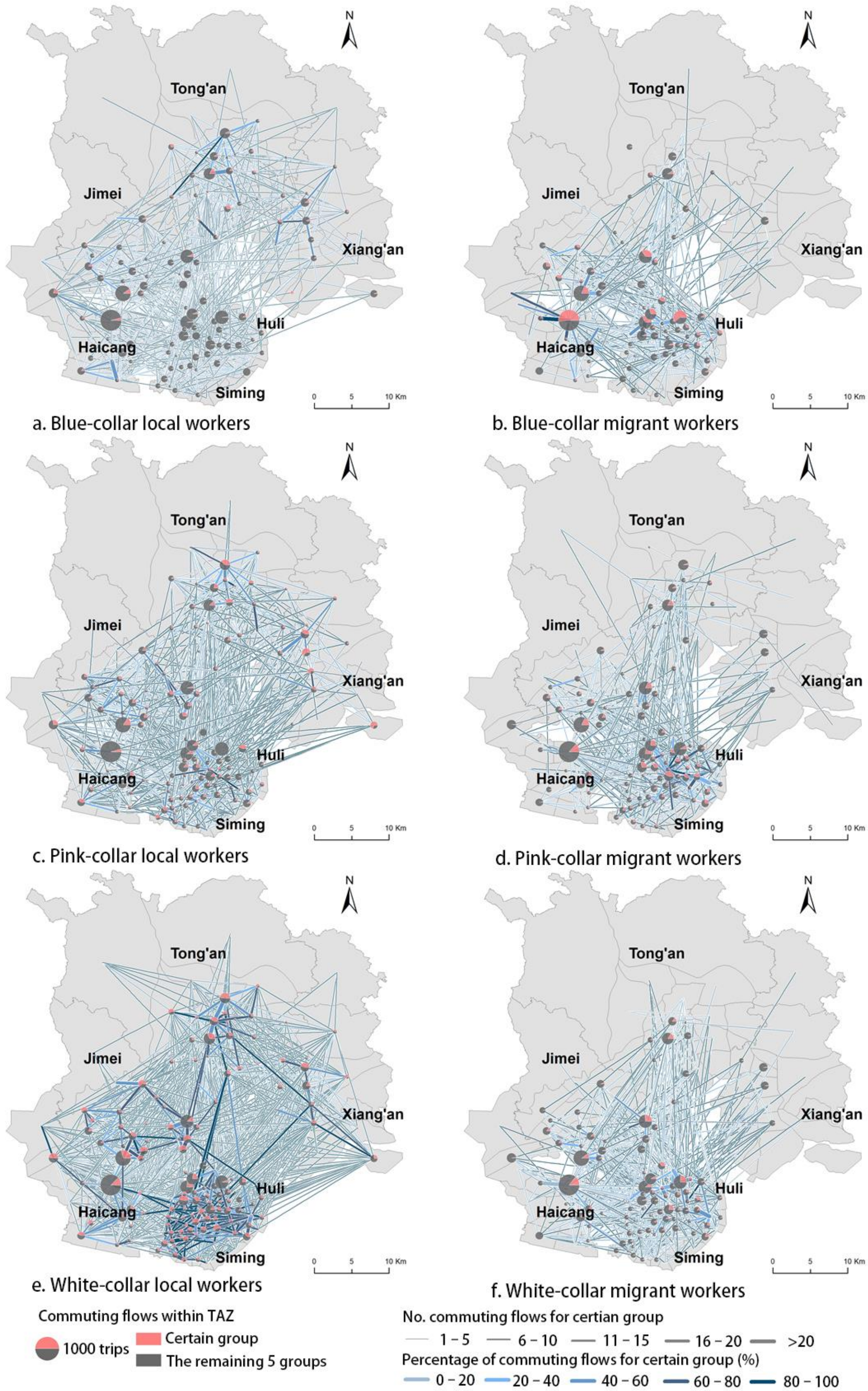

Figure 5.4 Commuting flows of workers by occupation

Notes: the size of the circle in the pie charts represents the total commuter flow of the six groups; The certain group is consistent with the layer name.

5.5 Results

Table 5.4 shows the effects of spatial and socioeconomic factors on commuting time and commuting distance, and how they affect differently between locals and migrants. Since the distribution of the dependent variables does not follow a normal distribution, we normalize the variables by applying a logarithmic transformation. Models 1 and 5 present the simple results for all sample groups while Models 2 and 6 present the result with interaction effects between *hukou* and occupation. The results of the spatial analysis show that the commuting pattern of the local workers is very different from that of the migrant workers. Therefore, we perform regression models on these two groups separately (Models 3 and 4 for commuting time and Models 7 and 8 for commuting distance).

Table 5.4 Regression of the natural logarithm of commuting time and commuting distance

	Commuting time				Commuting distance			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Total	Total	Locals	Migrants	Total	Total	Locals	Migrants
Job accessibility by public transportation	0.003***	0.003***	0.004***	0.004***	0.001	0.001	0.001	0.002**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Job accessibility by walking	-0.007***	-0.007***	-0.008***	-0.008***	-0.018***	-0.018***	-0.018***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Living in Xiamen Island (ref: no)	0.160***	0.159***	0.200***	0.067**	0.104***	0.101***	0.094***	0.086**
	(0.017)	(0.017)	(0.020)	(0.029)	(0.023)	(0.023)	(0.028)	(0.040)
Population density	-0.001	-0.001	-0.016**	0.043***	0.027***	0.028***	-0.003	0.090***
	(0.006)	(0.006)	(0.007)	(0.011)	(0.008)	(0.008)	(0.010)	(0.014)
Job density	-0.019*	-0.019*	0.018	-0.110***	-0.059***	-0.060***	0.002	-0.176***
	(0.011)	(0.011)	(0.013)	(0.022)	(0.016)	(0.016)	(0.019)	(0.030)
Bus stop density	0.001	0.001	0.002**	-0.001	-0.001	-0.000	0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Road density	0.003***	0.003***	-0.000	0.006***	0.001	0.001	-0.003**	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Gender	-0.125***	-0.123***	-0.140***	-0.090***	-0.287***	-0.283***	-0.304***	-0.242***
	(0.007)	(0.007)	(0.009)	(0.013)	(0.010)	(0.010)	(0.012)	(0.018)
Age	-0.007***	-0.007***	-0.009***	-0.004***	-0.010***	-0.010***	-0.013***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education level (ref: without college degree)								
College degree	0.120***	0.122***	0.117***	0.115***	0.180***	0.184***	0.173***	0.199***
	(0.009)	(0.009)	(0.010)	(0.020)	(0.013)	(0.013)	(0.015)	(0.027)
Master or above	0.111***	0.116***	0.098***	0.173**	0.161***	0.173***	0.152***	0.284**
	(0.025)	(0.025)	(0.027)	(0.074)	(0.037)	(0.037)	(0.039)	(0.115)
Household size	-0.001	-0.001	-0.003	-0.002	0.025***	0.024***	0.014**	0.031***
	(0.003)	(0.003)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)	(0.008)
Home ownership	0.080***	0.076***	0.042***	0.151***	0.206***	0.192***	0.125***	0.291***

	(0.012)	(0.012)	(0.015)	(0.019)	(0.016)	(0.016)	(0.021)	(0.027)
Urban village (ref: no)	-0.027**	-0.027**	-0.089***	0.050***	-0.067***	-0.065***	-0.120***	-0.037
	(0.012)	(0.012)	(0.016)	(0.018)	(0.016)	(0.016)	(0.023)	(0.025)
Occupation (ref: white-collar worker)								
Blue-collar worker	0.022**	-0.041**	0.068***	-0.055***	-0.044***	-0.205***	0.072***	-0.181***
	(0.011)	(0.016)	(0.015)	(0.017)	(0.015)	(0.022)	(0.020)	(0.024)
Pink-collar worker	-0.001	-0.056***	0.022**	-0.059***	-0.062***	-0.135***	-0.046***	-0.138***
	(0.009)	(0.015)	(0.010)	(0.016)	(0.012)	(0.021)	(0.014)	(0.022)
Hukou (ref: migrant)	-0.019	-0.064***			0.081***	0.002		
	(0.012)	(0.015)			(0.017)	(0.020)		
Blue-collar worker* *Hukou*		0.103***				0.287***		
		(0.021)				(0.029)		
Pink-collar worker* *Hukou*		0.076***				0.094***		
		(0.018)				(0.025)		
Constant	3.274***	3.307***	3.388***	3.142***	8.862***	8.927***	9.229***	8.502***
	(0.024)	(0.025)	(0.033)	(0.040)	(0.033)	(0.034)	(0.046)	(0.055)
Observations	34,372	34,372	23,340	11,032	34,372	34,372	23,340	11,032
R-squared	0.074	0.075	0.089	0.058	0.067	0.069	0.058	0.062

Note: *p<0.1; **p<0.05; ***p<0.01

In terms of our control variables, the positive and negative effects of each variable on commuting time and distance are similar for all models. In general, job accessibility by public transportation is positively related to commuting time and distance, while job accessibility by walking is negatively related to commuting time and distance. The results suggest that people tend to work at a closer distance if a lot of jobs are within walking distance and work in a larger area if a lot of jobs are within reach of public transportation. Living in Xiamen Island is positively related to commuting time and distance, indicating that residents on Xiamen Island suffer longer commuting time than those on the mainland districts. Regarding population density, it has different effects on local workers and migrant workers. For migrants, it appears that population density is positively related to commuting time. One possible explanation is that migrants prefer to stay in centrally located urban villages where may be far away from their working place because there is cheap housing for rent as well as social networks, through which they can obtain reciprocity resources (Zhu, 2015). For locals, by contrast, population density appears to be negatively correlated with commuting time. Unlike migrant workers who are distributed in specific areas, local workers are distributed in all corners of the city, including urban fringe areas with low population density and inconvenient transportation. Therefore, for locals, low density often leads to long commuting time. In line with previous studies (Zhou et al., 2014), job density is negatively related to commuting time and distance. In accordance with the present results, previous studies (Johnston-Anumonwo, 1992; Turner & Niemeier, 1997) found that females commute less than males, as mothers perform most of the housework and childcare. As expected, commuting time and distance decrease with age (Ham et al., 2001; McQuaid & Chen, 2012). In accordance with previous observations (Cassel et al., 2013), higher education increases commuting time and distance. In addition, bigger household size leads to considerably longer commuting distance, which is also in line with previous studies (Hu et al., 2018). Regarding home ownership, homeowners commute longer time and distances than renters. The underlying reason provided for this in the literature is that homeowners are much less likely to move than renters, as being a homeowner requires a substantial long-term financial commitment (Dieleman, 2001; Helderman et al., 2004). In contrast, renters are more flexible and more likely to choose a residential location near their workplace.

In terms of our focus variables, the results show that there is a big difference between the local workers and the migrant workers. Although Model 1 shows that the effect of *hukou* on commuting distance is not significant, the effect of *hukou* on commuting distance becomes significant after the interaction term is added (Model 2), indicating that the effect of *hukou* is dependent on the occupation. Since the results of Model 2 (or Model 6) are consistent with the results of Models 3 and 4 (or Models 7 and 8), we use the latter to interpret the results. For locals (Models 3 and 7), blue-collar workers commute longer times and distances than white-collar workers. Figure 5.3 shows that most local blue-collar workers are distributed in the outer urban areas, while industrial areas are concentrated in very few specific places, which are highly overlapped with the living distribution of migrant workers. This spatial mismatch for local blue-collar workers increases their commuting time and distance. Pink-collar local workers have longer commuting time, but shorter commuting distance than white-collar local workers. On the one hand, white-collar workers are more likely to be long-distance commuters (Aguiléra & Proulhac, 2015). This can be attributed to the selectivity of their potential jobs (job-labor match). On the other hand, due to income restrictions, pink-collar local workers will choose public transportation instead of private cars, which increases their commuting time accordingly (Appendix 1). For migrants (Model 4 and 8), blue-collar and pink-collar workers commute over shorter distances and times than white-collar workers. This may be due to an easier job-labor match for blue- and pink-collar workers than for white-collar workers, whose specialized jobs are mostly more limited and more concentrated in certain areas. In addition, the interaction effect shows (Models 2 and 6) that blue-collar locals commute longer times (-0.041-0.064+0.103=-0.002) and distances (-0.205+0+0.287=0.082) than blue-collar migrants (-0.041+0+0=-0.041 and -0.205+0+0=-0.205, respectively). In the same way, it can be seen that the commuting time and commuting distance of pink-collar local workers are longer than that of pink-collar migrant workers.

Models 3,4,7, and 8 show that for locals, living in an urban village has a negative impact on the commuting time and distance (= shorter commuting time and distance), while for migrants living in an urban village has a positive impact on the commuting time but a negative impact on the commuting distance (= longer commuting time but shorter commuting distance). Locals living in urban villages can be divided into indigenous villagers and local urban *hukou* holders (He et al., 2010). Low-skilled indigenous villagers are often unable to find more regular jobs in cities and therefore choose to make a living by renting houses there, while most urban *hukou* holders are employees of small street-run state-owned enterprises or collective-owned enterprises, who rent houses in nearby urban villages. Therefore, compared with locals living in other places, locals living in urban villages have shorter commuting times and distances. Urban villages also provide many employment opportunities, most of which are the informal service sector and retail sector (He et al., 2010). Therefore, a portion of the migrants can be employed within the urban villages. However, the migrants living in urban villages do not have an advantage in the commuting distance over the migrants living in other places, because the latter is likely to rent a living space nearby the workplace. Furthermore, compared to migrants living in other places, migrants living in urban villages are more vulnerable (e.g., the threat of demolition; lack local advantages due to their rural *hukou*) and are often at a disadvantage in terms of transportation, resulting in longer commuting time. Compared with locals, migrants commute shorter distances, but they do not have any advantage in commuting time (Models 1 and 5). Migrants are mostly renters who have great freedom in housing choice and movement, and therefore they tend to be more spatially matched than locals. However, as a vulnerable group, they are often at a disadvantage in terms of transportation and thus fail to reduce their commuting time accordingly.

5.6 Conclusions

To remedy the lack of insight into the actual spatial mismatch in China, the present research examined the commuting behavior of three groups of local and migrant workers in Xiamen, China, divided into blue-collar, pink-collar, and white-collar workers.

The main finding of this study is that there are differences in commuting distance and time among different types of workers. In line with other Chinese case studies (Li & Liu, 2016; Zhu et al., 2017), the descriptive statistics show that migrant workers commute shorter distances than local workers. Moreover, migrant workers mainly live in rental housing, which makes them more flexible than locals, who are mostly homeowners. Based on these outcomes, one would expect that migrant workers possess a much lower degree of spatial mismatch than local workers.

Although these outcomes are correct for the full populations of migrant and local workers in Xiamen, for a more correct picture one has to differentiate within these populations according to their occupation. By differentiating between blue-, pink- and white-collar workers, it shows that blue-collar local workers commute over longer distances than white-collar local workers because of the greater spatial mismatch of blue-collar local workers. Due to the income restrictions, pink-collar local workers tend to choose public transportation instead of private cars (Appendix III) and therefore commute more time but shorter distances than white-collar local workers. In terms of migrants, blue- and pink-collar workers commute over shorter distances and time than white-collar workers because of an easier job-labor match for blue- and pink-collar workers than for specialized white-collar workers whose jobs are mostly more limited and more concentrated in certain areas.

The findings from this study make several contributions to the literature. First, they show that workers with different occupations have different commuting behaviors, which have been overlooked by many existing studies on Chinese commuting patterns. Industrial relocation (suburbanization) after the 2000s and the rise of local peasant-workers living in peripheral cities have resulted in a spatial mismatch for blue-collar local workers. As a consequence, this group has the longest commuting distance and time, in contrast to pink-collar local workers, who enjoy the shortest commuting distance and time. However, migrant workers have a different commuting pattern. Both blue- and pink-collar migrant workers commute less than white-collar migrant workers do. The probable reason for this is that white-collar jobs are more specialized and concentrated, and white-collar migrants can afford to pay the associated higher travel costs (Sermons & Koppelman, 2001). These findings have significant implications for understanding how different occupational groups differ in their job-housing relationship.

Second, our findings shed new light on the role of urban villages in the job-housing balance. Living in an urban village has a negative impact on the commuting time and distance of locals, while it has a positive impact on the commuting time of migrants. Locals living in urban villages can be divided into indigenous villagers and local urban *hukou* holders, all of whom work in or near the urban village (He et al., 2010). Because most of the migrants living in urban villages are vulnerable groups, they are often at a disadvantage in terms of transportation compared to migrants living in other places, resulting in longer commuting time.

The findings in the present study have several policy implications. These policies are mainly to reduce the commuting time of disadvantaged groups because it has been proved that long commuting time has a negative impact on employment and the commuters' well-being (Sha et al., 2020). First, urban villages not only provide cheap rental housing but also provide low-skilled jobs, thus achieving a certain degree of job-housing balance. Therefore, redevelopment plans need to ensure the re-establishment of the job-housing balance in the original area to avoid future spatial mismatch. Second, given that most of the migrants in the inner-city urban village are blue- and pink-collar migrants, the demolition of urban villages may cause a large number of these two groups to gather in the suburbs. Unlike relocated blue-collar workers who can find more jobs in the suburbs, relocated pink-collar workers are more likely to commute to the inner city because pink-collar jobs are concentrated there. Therefore, the settlements after their relocation should be provided with efficient public transportation to link the Xiamen Island with the mainland districts. Third, migrants—regardless of occupation—tend to cluster together, and the resulting agglomeration effect and the homogeneity of social space may cause negative effects such as residential segregation, but also allows planners and decision-makers to target planning according to different spatial distributions of socioeconomic attributes. For example, since walking, cycling, and public transportation account for more than 90% of the modal split of blue- and pink-collar migrant workers, policymakers should ensure an adequate supply of public transportation and shared bicycles in their agglomeration areas. Fourth, the advantage of migrants in the commuting distance is due to the greater flexibility in living place as renters. Policymakers should therefore consider providing a certain proportion of low-rent housing for migrants.

A limitation of this study is that our study is a cross-sectional study, not a panel study. Therefore, to a certain extent, it reflects the correlation between dependent variables and independent variables, rather than the causal relationship between them.

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6. The influence of age, *hukou*, and occupation on long-distance commuting: Disentangling the effects of residential self-selection

ABSTRACT

This paper explores the spatial and commuting behavior of different socioeconomic groups in Xiamen, China. Heckman's sample selection model was applied to the data from the 2015 Xiamen household travel survey to separate the effect of socioeconomic factors, especially age, *hukou*, and occupation, and that of residential selection. Results show that the continued suburbanization of the industry attracted substantial numbers of young blue-collar workers to live in the outer districts (Haicang, Jimei, Tong'an, and Xiang'an), and thus young blue-collar workers are less likely than young pink- and white-collar workers to commute to the inner districts (Siming and Huli). In addition, the probability of multi-worker households living in the outer districts increases with age. In terms of people living in the inner districts, the probability of blue-collar workers commuting to the outer district increases with age. Moreover, the inner-district migrants (mostly renters) are less likely to commute to the outer districts than the inner-district locals (mostly homeowners).

Keywords: Heckman's sample selection, spatial mismatch, long-distance commuting, residential choice

6.1 Introduction

The invention of the steam railway during the nineteenth century resulted in the first large-scale separation of work and residence and long-distance commuting in Europe and the United States (Heblich et al., 2020). Before the 19th century, most workers in Europe and the United States lived within an hour's walk from the workplace. The industrial revolution and advances in transportation technology led to urban expansion and the rise of suburbs (Mauss et al., 2016). It is not just the expansion of cities that has given rise to long-distance commuting; in turn, commuting has had a substantial impact on modern life, allowing cities to grow to sizes that were previously infeasible and leading to the proliferation of suburbs.

In China, the separation of work and residence has emerged with the market-oriented transformations since the late 1970s and the disintegration of the *danwei* system—which once provided workplaces, housing, and facilities for workers at the same location (Liu & Chai, 2015). Over the past three decades, the continuous process of industrialization and suburbanization has created new urban spaces in both inner cities and outer cities, leading to substantial changes in the original urban spatial pattern. Furthermore, China has experienced extensive housing reforms following the disintegration of the *danwei* (work unit) system, which led to the separation of work and residence and generated commuting flows (Chai et al., 2011). Currently, there are three major commuting patterns in China: commuting from city centers to suburbs, commuting from suburbs to city centers, and commuting between suburbs (Ta et al., 2017). Since most Chinese cities are still characterized by monocentric urban structures, large numbers of commuting flow from suburbs to centers are generated, especially from the large residential communities (Lin, Allan, & Cui, 2015; Sun, Pan, & Ning, 2008). In contrast, those who lived in old urban areas and work in the new urban areas (emerging suburbs) generate a commuting flow from city centers to the suburbs (Chai et al., 2008).

The commuting pattern is the result of the combined effect of the urban form and the personal socioeconomic attributes. Considerable differences may exist between socioeconomic groups in terms of their commute patterns because they have different spatial characteristics in different historical periods. Suburbanization, the new housing system, and the continuous flow of migrants to the cities have led to the increasing concentration and segregation of different socioeconomic groups (Fan et al., 2014; Qi et al., 2018). A large proportion of the reverse commute is caused by industrial suburbanization, and there may be some differences between people with different occupations. For example, blue-collar workers are more likely to be the reverse commuter than other occupations, especially those who owned homes in the inner city during the industrial suburbanization. In addition, differences may exist between the older generation who experienced the housing reform and the disintegration of the *danwei* system, and the younger generation born after that. After housing system reform in 1998, the older generation began to buy relatively "affordable" housing in the inner city (Wu et al., 2002), while the younger generation was often forced to reside in suburbs due to the high price in the inner city (Wu et al., 2002; K. Zhou & Yang, 2008). Moreover, large variations may exist between people with local *hukou* (a system of household registration) and non-local *hukou*. After market-oriented transformations and related institutional changes, large numbers of migrants have flocked to the cities, mainly engaging in labor-intensive industries and living in urban villages, which are also known as "villages in the city" (ViCs)[7] (Lin & Gaubatz, 2017). Unlike the migrants who are concentrated in specific areas, the locals are distributed over a much larger urban space. These spatial differences will lead to differences in their commuting behaviours and resulting patterns.

The inconsistency of travel patterns among different groups is not only directly affected by socioeconomic attributes but also by their choice of the residential area. Zhou *et al.* (2016) found that blue-collar workers are mainly concentrated in exurban areas while white-collar workers are distributed in the central urban area. Even though these differences in residential distribution may lead to differences in travel patterns, previous studies paid hardly any attention to this aspect. To study the different moderating effects

[7] A ViC was originally a rural settlement that in the process of continuous urbanization was encapsulated by a growing city and now forms an urban neighborhood of that city. ViCs are usually "managed" by the original villagers (Lin et al., 2014).

of socioeconomic status on residential choice and long-distance commuting in China, this research conducts an exploratory analysis of the extent to which age, *hukou*, occupation, and their interaction determine the long-distance commuting when controlling for residential choice. We choose cross-district commuting as the index of long-distance commuting because the relationship between the outer districts and the inner districts in Xiamen is very similar to the relationship between the inner city and the suburbs. The understanding of cross-district commuting in Xiamen can help the policymakers to develop more reasonable housing policies and spatial strategies. With this intention, the 2-step model was conducted by examining determinants of residential choice in the first step and determinants of long-distance commuting in the second step.

Following the introduction, the rest of the paper is structured as follows. In Section 2, we present a review of the existing literature. In Section 3, we briefly introduce the study area and the 2-step model. Section 4 is dedicated to the results of the model outcomes for Xiamen. The conclusions and findings are presented in Section 5.

6.2 Literature review

6.2.1 Determinants of residential location choice

Recent studies also show that commuting behavior can be explained by the self-selection hypothesis. Households may not only align their commuting behavior to constraints of their residential location but also can self-select their residential locations according to their travel-related attitudes (Bohte et al., 2009). For instance, individuals who prefer to use a car could choose environmentally friendly locations as their residential areas (Zhao, 2015), while individuals who could not afford private cars may opt for more urban residential locations where they can avoid long-distance commuting.

Previous research has shown that socioeconomic traits constrain abilities and needs, and thus influence individuals' residential self-selection (Mokhtarian & Cao, 2008). Handy *et al.* (2005) reported that the average age is older in suburban areas than traditional ones in Northern California. In contrast, old people in China are more likely to live in the old city while young people are being migrated to suburbs (Liu & Zhang, 2006; Wu et al., 2002). Schwanen and Mokhtarian (2007) found that bigger household sizes tend to live in the suburban area, while smaller households tend to live in the city. Similar results are found in Handy et al. (2005). Besides, housing ownership also influences residential location choice. Cao (2009) found that compared to renters, homeowners are more likely to choose suburban neighborhoods than traditional ones. Another example is found by Handy *et al.*(2005): the percentage of homeownership is higher in suburban neighborhoods than in traditional ones. Education level and worker type are associated with the residential location choice. For instance, using a concentration index, Zhou *et al.* (2016) presented the types and spatial distribution of the social areas in Guangzhou in 2010 and finds that blue-collar workers mainly concentrated in exurban areas while white-collar workers are distributed in the central urban area. They also find that higher education groups reside in the central urban area. Similarly, Tran *et al.* (2016) found that most labor-intensive workers live in suburbs while most knowledge-intensive workers live in the urban core in Hanoi, Vietnam.

Various evidence shows that location and neighborhood characteristics have a great influence on residential location choice. Most families prioritize urban amenities and transportation infrastructure in choosing their residential location choice (Acheampong, 2018). Population density has a negative effect on residential choice (Kim et al., 2005). In contrast, the employment-population ratio positively affects the residential location choice (Prashker et al., 2008). In addition, people prefer to live in places with shorter commutes and lower housing prices (Kim et al., 2005). Therefore, these variables need to be added to our model as focus variables and control variables.

6.2.2. Determinants of long-distance commuting

Data from several studies suggest that long-distance commuting decreases with increasing age (McQuaid & Chen, 2012; van Ham et al., 2001). Amcoff (2009) found for Sweden that young adults (15–24 years old) have the longest average commuting distance. Others argue that the influence of age is not that clear (Limtanakool et al., 2006; Maarten van Ham & Hooimeijer, 2009). In addition, some found that the relationship between age and long-distance commuting is non-linear, first increasing and then decreasing with age (Hu et al., 2018; Sandow & Westin, 2010). This suggests that the effect of age on long-distance commuting varies with age level and city, which needs to be further explored.

Several studies show that migration experiences also influence commuting behavior (Andersson et al., 2018). In Western countries, a large body of literature suggests that migrants are more likely than locals to commute longer distances. For instance, migrants in rural England are more likely than locals to exhibit long-distance commuting behavior (Champion et al., 2009). Similar results were found in the Netherlands (Van Ham & Hooimeijer, 2009). In contrast, in China migrants commute shorter distances than locals and tend to have better jobs-housing balance (Li & Liu, 2016) because they usually live in ViCs, most of which are close to industrial sites.

Numerous studies have examined the relationship between occupational attributes and long-distance commuting (Aguiléra & Proulhac, 2015; McQuaid & Chen, 2012). Aguiléra and Proulhac (2015) found that in France, employees with medium to high levels of responsibility (e.g., company directors and executives) were more likely to be long-distance commuters. Similarly, other authors (e.g., Champion et al., 2009; McQuaid & Chen, 2012) found that in the UK, those with higher-level occupations were considerably more likely to travel longer distances. To a large extent, this is because these management and professional occupations are spatially unevenly distributed (Öhman & Lindgren, 2003).

In addition, other individual and household attribute also determine long-distance commuting. A common finding is that men commute longer distances than women (Dargay & Clark, 2012; Guttman et al., 2018; Hu et al., 2018), as mothers taking the larger role in childcare and housework, leaving less time for commuting (Turner & Niemeier, 1997). In general, household size is negatively related to long-distance commuting. Dargay and Clark (2012) found that the more complex the family composition, the shorter commuting distances. In contrast, in Shanghai, Hu et al. (2018) found that it is positively related to long-distance commuting in Chinese cities. Having a university education increases the probability of long-distance commuting in Sweden since highly qualified jobs are more spatially concentrated, leading to the longer commuting distance to reach these jobs (Cassel et al., 2013). Another finding is that car ownership and housing ownership impact whether they engage in long-distance commuting. Generally, a family with a car is more likely to be a long-distance commuter than a family without a car (Champion et al., 2009; Limtanakool et al., 2006). Due to the high transaction costs, homeowners are less likely to migrate than renters (Dieleman, 2001; Helderman et al., 2004). Consequently, homeownership is positively related to long-distance commuting. Geographical attributes often influence long-distance commuting. Zhao et al. (2010) found that workers living in suburbs with a higher jobs-housing balance or higher population density were more likely to commute to other suburbs than to the central urban area. Their findings suggest that compact land development in the suburbs reduces the need for long-distance commuting to urban centers.

However, most studies on long-distance commuting focus on the socioeconomic traits of long-distance commuters, and relatively few have examined the self-selection effect of residential choice. Evidence suggests that there are residential self-selection issues that may overestimate the relationship between the built environment and travel behavior (Cao, 2009; Tran et al., 2016; Zhou & Kockelman, 2008). Long-distance commuting can be partly caused by the choice of residential location, but this has not been fully examined. In addition, relatively few studies have estimated interaction between age, *hukou*, and occupation for long-distance commuting, although the interaction between them has a policy significance. A detailed study of these interactions for different socioeconomic groups would provide a scientific basis for better spatial planning.

6.3 Methodology and data

6.3.1 Study area and data source

Xiamen is a large city with a permanent resident population of more than 4 million in 2019. The urban built-up area has spread from the southwestern coastal area on the island of Xiamen (inner districts, namely Siming and Huli), to all other districts (outer districts, namely Haicang, Jimei, Tong’an, and Xiang’an).

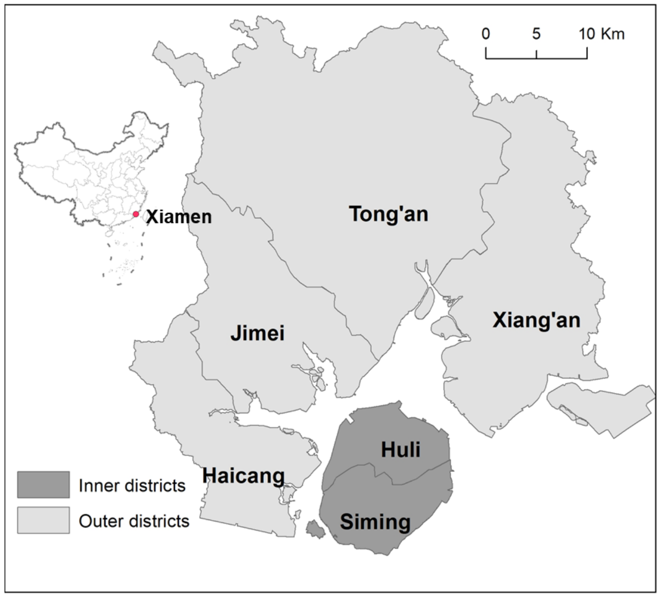

Figure 6.1 Xiamen city in China: location and administrative divisions

Before the 1980s, the population of Xiamen was mainly concentrated in the southwestern coastal area of Xiamen Island, with some small concentrations in Jimei School Village and Xinglin[8] Town. In 1980, Xiamen became one of China's original four special economic zones (SEZs), covering an area of 2.5 square kilometers in the current Huli District[9]. In 1984, the Xiamen SEZ was extended to the whole island (Siming and current Huli districts), now covering 131 square kilometers. Subsequently, the State Council authorized three Taiwanese investment zones that would enjoy the same policy of Xiamen SEZ in Haicang (1989), Jimei (1989), and Xinglin (1992). These three Taiwanese investment zones have played a prominent role in the development of Jimei and Haicang, promoting the transformation of the city from the "island city" in the 1980s to the "island–gulf city" in the 1990s (Cao & Liu, 2007). Since then, the industry in the inner districts has gradually moved to the outer districts, which accounted for two-thirds of the city's industrial output in 2014.

The data for this study were obtained from the 2015 Xiamen household travel survey conducted by the Xiamen urban planning and design research institute. A total of 40,201 households were selected and 120,603 individual travel survey forms were issued in this survey, which covers 3% of the total population of Xiamen. The survey covers household characteristics, individual characteristics, travel times, travel purpose, origin and destination, travel mode, travel time, travel distance, etc. After excluding respondents with missing data and data unrelated to commuting, we had data on 36,157 commutes, and these were included in our regression analysis.

[8] Xinglin District used to be a municipal district in Xiamen. It was established in September 1978 and divided into Haicang District and Jimei District in April 2003. Xinglin TIZ is currently located in Jimei District.

[9] Huli District was founded in November 1987 and is the place of origin of the Xiamen SEZ.

6.3.2 Method

Heckman's selection model is often used in traffic behavior research to separate the effect of the built environment from that of self-selection (Cao et al., 2009; Hong et al., 2014). The basic idea behind these sample selection models is to model the prior selection into binary states (inner vs. outer districts) in the first step, and then model the outcome of travel behavior (cross-district commuting vs. intra-district commuting) as a conditional on that prior selection in the second step (Cao et al., 2009). Since most of these models evaluate continuous variables in the second step, ordinary least squares (OLS) estimation is usually used in the second step model. However, as the second step dependent variable (whether to be a cross-district commuter) is binary in our model, we conducted a Heckman probit model, which enables the estimation of binary-dependent outcome variables. The Heckman probit procedure is conducted in STATA software, which can simultaneously estimate two bivariate probit regression models, for both the selection model and the outcome model.

In the first step, we analyzed separately the residential choices in the outer districts (outside Xiamen Island) and the inner districts (Xiamen Island). Although the outer districts are not suburbs in the strict sense of the word, they do have many suburban features: separated areas within commuting distance of the central inner-city areas; and in the process of suburbanization, in the sense that commercial, financial, and other tertiary industries cluster in Xiamen Island (inner districts), while labor-intensive industries are moving to the outer districts. Thus, here we make use of existing literature on the residential choice of suburbs to explain the mechanisms behind our results. In the second step, we analyzed whether those living in the outer districts commute to the inner districts or vice versa.

First, the selection equation (first stage) can be written as:

$$\mathrm{Y}_i^{\ select} = (\gamma \mathrm{Z}_i + \mu_{1i}) > 0 \quad (1)$$

Where $\mathrm{Y}_i^{\ select}$ represents the binary result of living in the inner or outer districts; Z_i and γ denote explanatory variables and corresponding coefficients in the first stage, respectively; μ_{2i} is the error term of the selection equation.

Second, the outcome model (second stage) can then be structured as follows:

$$\mathrm{Y}_i^{Profit} = \beta \mathrm{X}_i + \mu_{2i} > 0 \quad (2)$$

where Y_i^{Profit} is the binary outcome representing whether to be a cross-district commuter; X_i and β stand for explanatory variables and corresponding coefficients, respectively; μ_{1i} is the error term.

As explained, the second stage of estimation is conditional on the result of the first estimation and the two-step Heckman selection model can be described as follows (Plümper et al., 2006): first, use Eq. 1 to estimate the coefficient vector $\hat{\gamma}$ in the selection equation (first stage) for the overall sample. Second, compute the non-selection hazard (sometimes also called inverse Mills ratio) that measures the likelihood that a resident does not reside in the inner districts (or outer districts) in the first stage:

$$\widehat{\lambda_i} = \frac{\varphi(\hat{\gamma} Z_i)}{1 - \Phi(\hat{\gamma} Z_i)} \quad (3)$$

where $\widehat{\lambda_i}$ denotes the Inverse Mills Ratio; φ and Φ are the probability density function and cumulative distribution function of the standard normal distribution, respectively. Finally, $\widehat{\lambda_i}$ is considered as an additional regressor in Eq. 2 to estimate the probit model. In the Heckman probit selection model, the selection model (first stage) should have at least one variable that is not in the outcome model; otherwise, there is no structural explanation for the coefficient (StataCorp, 2019).

6.3.3 Variables

First stage variables (residential location choice)

The dependent variable in the first stage indicates whether the residents live in the outer or inner districts. In terms of independent variables, a variety of evidence supports location and neighborhood characteristics—such as population density, job-housing balance, accessibility, and housing prices—have a great impact on the residential location choice (Acheampong, 2018; Kim et al., 2005; Prashker et al., 2008). In addition, socioeconomic characteristics such as age, household income, household characteristics, education level, and occupation type determine residential location choice (Acheampong, 2018). However, since our dataset does not include income data, income was not selected as an independent variable. Moreover, consistent with previous studies (Kim et al., 2005; Sener et al., 2010), travel-related variables (such as commuting time) were also selected as independent variables.

Second stage variables (cross-district commuting)

The dependent variable in the second stage indicates whether the residents commute across districts. Our key independent variable of interest is age, *hukou*, occupation. We divided the occupation into three groups: blue-collar workers, pink-collar workers, and white-collar workers. Blue-collar workers are production workers and transport equipment operators; pink-collar workers are business and service personnel; and white-collar workers are unit heads, professional and technical experts, and clerks and related workers. Other influencing factors, including jobs-housing balance (Zhao et al., 2010), population density (Zhao et al., 2010), gender (Newbold et al., 2017), housing status (Helderman et al., 2004), household size (Dargay & Clark, 2012; Schwanen & Mokhtarian, 2007), education level (Cassel et al., 2013), and car ownership (Champion et al., 2009; Limtanakool et al., 2006) are selected as our control variables. The variables of the two steps are relatively independent, depending on the various determinants of each stage. The two-step statistical relationship is mainly based on the inverse Mills ratio, which measures the likelihood that a resident does not reside in the inner districts (or outer districts) in the first stage, and is incorporated into the model in the second stage as an additional regressor.

Table 6.1 Summary statistics of explanatory variables

Variables	Description	Mean/proportion	Std. Dev.
Location variables			
Population density	The net density of population where a worker lives in the TAZ (10,000 persons/km^2)	1.946	1.390
Employment–population ratio	The distribution of employment relative to the distribution of population in the TAZ	0.521	0.177
Bus stop density	The net density of bus stops per kilometer where a worker lives in the TAZ	5.420	3.337
Average housing value	Average housing value in each administrative district	3.918	1.157
Socioeconomic variables			
Gender	Male (reference)	56.71%	
	Female	43.29%	
Education level	Without college degree (reference)	74.73%	
	With college degree	23.37%	
	Master's degree or higher	1.90%	
Household size	Number of household members		
Household composition	One-worker household	14.37%	
	Two-worker household	63.14%	
	Three or more-worker household	22.49%	
Housing status	Owner-occupied housing (reference)	66.60%	
	Rental housing	32.25%	
	Danwei housing	1.14%	
Car ownership	Without car	55.67%	
	With car	44.33%	
Hukou	Local (reference)	68.20%	
	Migrant	31.80%	
Age	Age	35.857	8.912
Occupation	Blue-collar worker	16.15%	
	Pink-collar worker	30.63%	
	White-collar worker (reference)	53.22%	
Travel-related variables			
Commuting time	Commuting time (min)	28.763	19.743

6.4 Results

Consistent with our theoretical model, the empirical analysis adopts the two-stage model. In the first stage, the residential choices of residents living in the outer districts were endogenized. Then, the estimated probability of not living in the outer districts is used as a regressor in the second stage to analyze the possibility of commuting from the outer districts to the inner districts. Table 6.2 presents the selection results for the choice of living in the outer districts.

Table 6.2 Binary probit model for the choice of living in the outer districts (first stage)

	Model 1-1		Model 2-1	
	Coef.	Robust SE	Coef.	Robust SE

Population density	-0.075***	0.02	-0.076***	0.02
Employment–population ratio	0.084	0.116	0.087	0.116
Bus stop density	-0.059***	0.01	-0.060***	0.01
Average housing value	-2.826***	0.067	-2.830***	0.066
Commuting time	-0.002	0.001	-0.002	0.001
Gender (ref: male)				
Female	-0.000	0.034	0.002	0.034
Education level (ref: without college degree)				
With college degree	-0.008	0.057	-0.002	0.057
Master's degree or higher	0.329*	0.196	0.318	0.195
Household size	0.002	0.019	0.004	0.02
Housing status (ref: owner-occupied housing)				
Rental housing	-0.113*	0.065	-0.118*	0.065
Danwei housing	-0.189	0.164	-0.186	0.165
Car ownership	0.014	0.046	0.010	0.046
Age	0.006***	0.002	0.002	0.005
Household composition (ref: one-worker household)				
Two-workers household	0.126**	0.054	-0.211	0.246
Three or more-worker household	0.149**	0.074	-0.337	0.262
Hukou (ref: local)				
Migrant	0.059	0.067	-0.075	0.204
Occupation (ref: white-collar worker)				
Blue-collar worker	0.090**	0.038	0.598***	0.175
Pink-collar worker	-0.126***	0.041	0.003	0.198
Interaction effect				
Household composition×Age				
Two-workers household×Age			0.009*	0.005
Three or more-worker household×Age			0.013**	0.005
Household composition×*Hukou*				
Two-workers household×Migrant			0.072	0.122
Three or more-worker household×Migrant			0.057	0.14
Occupation×Age				
Blue-collar worker×Age			-0.016***	0.004
Pink-collar worker×Age			-0.004	0.005
Hukou×Age				
Migrant×Age			0.001	0.004
Hukou×Occupation				
Migrant×Blue-collar worker			0.078	0.085
Migrant×Pink-collar worker			0.043	0.085
Constant	10.414***	0.254	10.620***	0.33

Note: *p<0.1; **p<0.05; ***p<0.01

In terms of location variables, population density, bus stop density, average housing value are negatively associated with those living in the outer districts, which is in line with our expectation. Regarding socioeconomic factors, consistent with previous studies, highly educated residents, and homeowners tend to reside in the outer districts (Cao, 2009).

With respect to our focus variables, Model 2-1 explains the influence of age, household composition, *hukou*, and occupation on residential location choice under the interaction of each other. Since the interaction between household composition and occupation is not significant in all 2-step models, we did not include the interaction terms of these two factors in the final model. Only the main effect of occupation is statistically significant. In line with our expectation, blue-collar workers are more likely to reside in the outer districts than white-collar workers, since emerging blue-collar jobs are concentrated in the outer districts. Interaction effects show that the effect of age changes with occupation and household composition (Figure 6.2). Younger blue-collar workers are more likely than older blue-collar workers to live in the outer districts as a result of the continued suburbanization of industry over the past two decades. Given that most pink-collar and white-collar jobs concentrated in the inner districts, these two groups prefer to live in the inner districts. However, with the increase of age and the change of household composition (Figure 6.2(b)), their demand for owner-occupied housing increases. Considering the purchasing power of housing, they are more willing to live in outer cities. Therefore, older pink- and white-collar workers are more likely than younger pink- and white-collar workers to live in the outer districts due to the lifecycle effects and housing affordability.

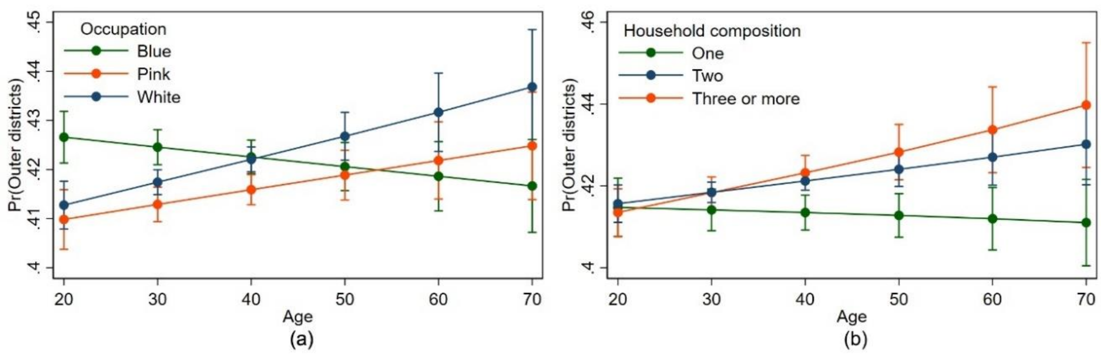

Figure 6.2 Interaction effects on the choices of outer-district neighborhoods

Table 6.3 presents the results of the regression analysis of cross-district commuting (outer-to-inner flow and inner-to-outer flow). Four separate regressions were estimated for cross-district commuting: two used the sub-sample of residents living in the outer districts and the other two used the sub-sample of residents living in the inner districts.

Table 6.3 Binary probit model for cross-district commuting (second stage)

	Outer-to-inner flow				**Inner-to-outer flow**			
	Model 1-2		Model 2-2		Model 3-2		Model 4-2	
	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE
Population density	0.155***	0.015	0.157***	0.015	0.032***	0.009	0.033***	0.009
Employment–population ratio	-0.028	0.128	-0.021	0.129	0.151***	0.058	0.145**	0.058
Gender ref: male								
Female	-0.242***	0.028	-0.245***	0.028	-0.200***	0.025	-0.197***	0.026
Education level (ref: without college degree)								
With college degree	0.465***	0.034	0.463***	0.035	0.008	0.029	0.007	0.029
Master's degree or higher	0.364***	0.126	0.368***	0.126	0.151**	0.069	0.157**	0.069

Household size	-0.019	0.014	-0.025*	0.015	0.043***	0.013	0.039***	0.013
Housing status (ref: owner-occupied housing)								
Rental housing	-0.192***	0.059	-0.149**	0.059	-0.084**	0.039	-0.069*	0.039
Danwei housing	-0.670***	0.243	-0.694***	0.243	0.120	0.089	0.113	0.089
Car ownership	0.258***	0.03	0.256***	0.03	0.206***	0.028	0.206***	0.028
Age	-0.018***	0.002	-0.012**	0.005	0.007***	0.001	0.006	0.004
Household composition								
Two-workers household	-0.022	0.051	0.370*	0.209	0.015	0.037	-0.015	0.151
Three or more-worker household	-0.003	0.062	0.137	0.213	-0.045	0.051	-0.066	0.17
Hukou (ref: local)								
Migrant	0.076	0.055	-0.248	0.17	-0.076*	0.04	-0.303**	0.133
Occupation (ref: white-collar worker)								
Blue-collar worker	-0.205***	0.042	-0.486***	0.169	0.077*	0.041	0.121	0.18
Pink-collar worker	0.066**	0.033	0.254*	0.133	-0.219***	0.03	0.011	0.128
Interaction effect								
Household composition×Age								
Two-workers household×Age			-0.013**	0.005			0.000	0.004
Three or more-worker household×Age			-0.007	0.005			-0.000	0.004
Household composition×*Hukou*								
Two-workers household×Migrant			0.164	0.101			0.053	0.074
Three or more-worker household×Migrant			0.259**	0.118			0.085	0.095
Occupation×Age								
Blue-collar worker×Age			0.011**	0.004			0.004	0.004
Pink-collar worker×Age			-0.004	0.004			-0.007**	0.003
Hukou×Age								
Migrant×Age			0.008*	0.004			0.007**	0.003
Hukou×Occupation								
Migrant×Blue-collar worker			-0.302***	0.086			-0.407***	0.084
Migrant×Pink-collar worker			-0.188**	0.076			-0.004	0.063
Constant	-0.722***	0.109	-0.866***	0.217	-1.761***	0.088	-1.711***	0.157

Note: *p<0.1; **p<0.05; ***p<0.01

Model 1-2 and Model 2-2 show the results of cross-district commuting (second stage) by workers who reside in the outer districts, which confirm the existence of selection effects. The coefficient rho[10] (0. 310 for both Model 1-2 and Model 2-2) of the test for

[10] Rho—which is the correlation between the regression and the selection equation—is bound between -1 and 1.

independence of equations is statistically significant at the 0.01 level, indicating that living in the outer districts is pertinent to cross-district commuting.

In terms of our control variables, population density, gender, education level, housing status, and car ownership are correlated to cross-district commuting. The probability of cross-district commuting is lower for females, which is in line with the literature (Cassel et al., 2013; Zhu et al., 2017). In accordance with previous studies, higher education levels increase the probability of cross-district commuting, as jobs requiring higher education are scarcer and their distribution is more concentrated (Cassel et al., 2013). In addition, the probability of cross-district commuting is lower for residents living in the rental or *danwei* housing, because low transaction costs allow renters to move closer to work (Dieleman, 2001; Helderman et al., 2004). As expected, car ownership is positively related to cross-district commuting. The impact of the household composition on cross-district commuting is not statistically significant in Model 1-2, but it will have an impact after adding the interaction term in Model 2-2.

Model 2-2 indicates that the main effect of age is negative, which is consistent with existing studies (McQuaid & Chen, 2012; van Ham et al., 2001). The main effect of occupation is also significant. Blue-collar workers are less likely than white-collar workers to commute from the outer districts to the inner districts since the emerging blue-collar jobs are concentrated in the outer districts, while most white-collar jobs are concentrated in the inner districts. Compared with white-collar workers, pink-collar workers are less likely to reside in the outer districts (Table 6.2), but if they do live in the outer districts, they are more likely than white-collar workers to commute to the inner districts (Table 6.3), indicating that pink-collar jobs, for example, service and commercial sectors are more concentrated in the inner districts than white-collar jobs.

The interaction effects show that the effect of age changes with occupation and *hukou* (Figures 6.3(a) and 6.3(b)). Before the age of 50, pink-collar and white-collar workers are more likely to commute from the outer districts to the inner districts than blue-collar workers, whereas the results are the opposite after age 50. The opening of the Xiamen Bridge in 1991 and the development of industrial zones in the 1990s and early 2000s strengthened the connection between the inner districts and Xinglin, Jimei, and Tong’an districts (Cao & Liu, 2007). The reverse commuting caused by suburbanization that began 20 to 30 years ago has led to more cross-district commuting for older blue-collar workers than other occupations. In general, migrants are more likely to commute from the outer districts to the inner districts than locals with increasing age. As mentioned above, the transformation from "island city" to "island–gulf city" started in the 1990s, and a large amount of local population gradually gathered in the outer districts from this period. With the allocation of large industrial zones and Taiwan investment zones in the outer districts, a large amount of the local population moved there, achieving a certain degree of job-housing balance. In contrast, the housing choices of people living in outer districts after the 2000s are likely to be affected by the low housing prices in outer districts after the housing reform. Unlike the local population, older migrants did not move to the outer districts 20-

30 years ago but are more likely to have migrated there in recent years. Therefore, their residential location choice is more likely to be caused by housing demand rather than employment-driven settlement. The interaction effects also reveal that the effect of occupation differs by *hukou*. For locals, the probability of commuting from the outer districts to the inner districts is highest for pink-collar workers and lowest for blue-collar workers, since blue-collar jobs are mostly concentrated in the outer districts and pink-collar jobs are mostly in the inner districts. In addition, the effect of household composition on outer-to inner flow differs by age and *hukou*. Multi-worker households are less likely than one-worker households to commute from the outer districts to the inner district with increasing ages (Figure 6.3(d)), especially for locals (Figure 6.3(e)). This may be due to the rapid development of the outer districts that began in the 1990s, which enabled the original farmers (often with extended family structures) in the outer districts to engage in other industries and accept emerging jobs there.

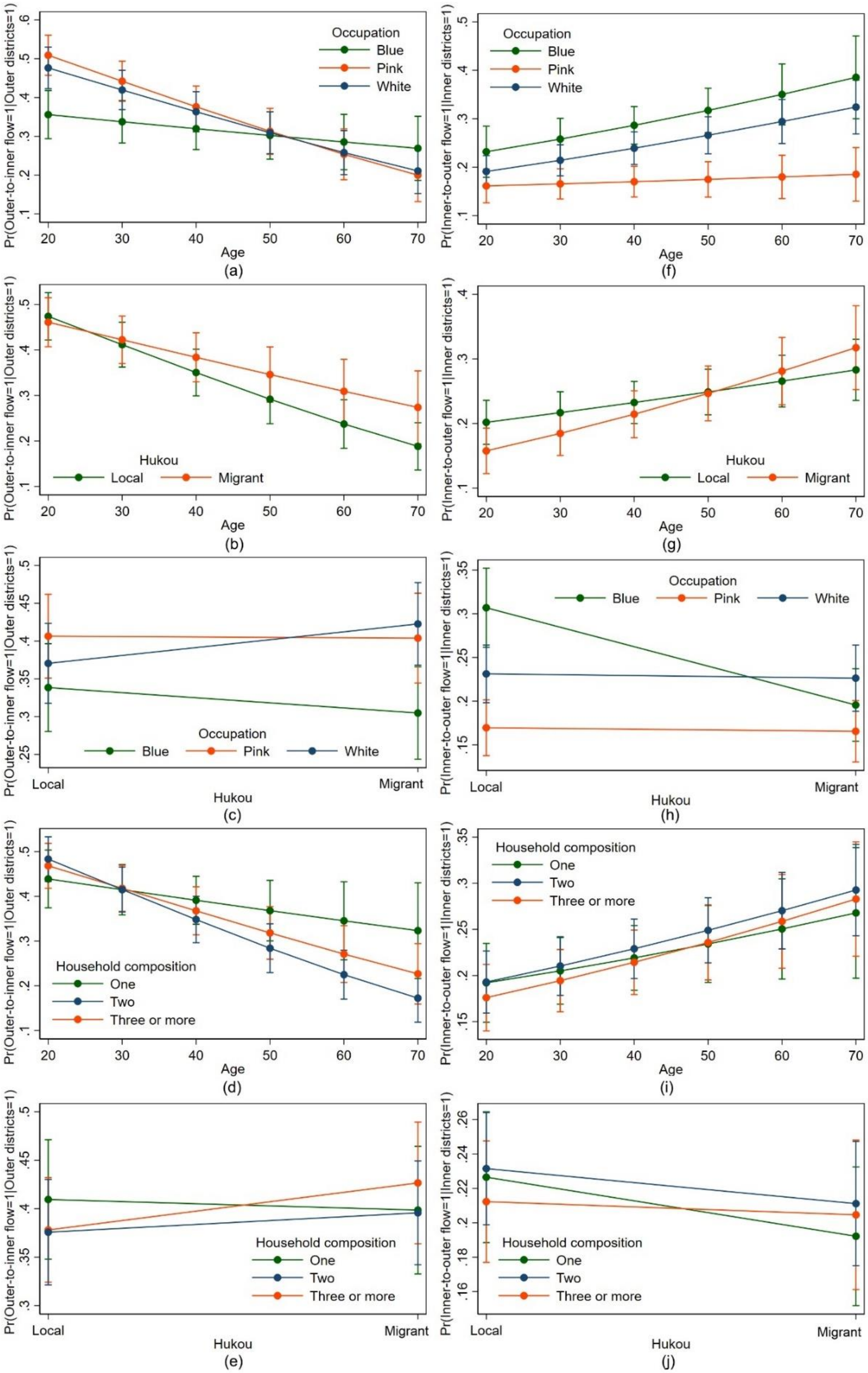
Pr(Outer-to-inner flow=1|Outer districts=1)
Pr(Inner-to-outer flow=1|Inner districts=1)
Age
Hukou
Local
Migrant
Occupation
Blue
Pink
White
Hukou
Local
Migrant
Household composition
One
Two
Three or more
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
(i)
(j)

Figure 6.3 Interaction effect on the cross-district commuting

The second model shows the results of cross-district commuting by workers who reside in the inner districts, which confirm the existence of selection effects. The coefficient rho (0.328 for both Model 3-2 and Model 4-2) of the test for independence of equations is statistically significant at the 0.01 level, indicating that living in the inner districts is pertinent to cross-district commuting.

In terms of our control variables, population density, gender, education level, housing status, and car ownership are correlated to inner-to-outer flow, and the positive and negative effects of these factors are consistent with outer-to- inner flow. After adding the interaction terms (Model 4-2), the main effects of age and occupation are statistically insignificant. The main effect of *hukou* indicates that migrants are less likely to commute from the inner districts to the outer districts since they choose to live in the inner districts mainly because of their jobs there.

Although Table 6.3 shows that the interaction between the household composition and other variables is not significant, this table omits the interaction for the reference groups (for instance the interaction effect of one-workers household×migrant), thus we use Figure 6.3 to illustrate the interaction between them. The interaction effects show that the effect of age changes with occupation and *hukou* (Figures 6.3(f) and 6.3(g)). The effect of age on blue-collar and white-collar workers is positive, but the effect on pink-collar workers is not obvious. The development of large industrial zones and Taiwan investment zones in the outer districts that started in the 1990s resulted in a certain degree of spatial mismatch between jobs and housing for blue-collar and white-collar workers in the inner districts. As a result, the older blue-collar and white-collar workers are, the more likely they are to commute from the inner districts to the outer districts. In contrast, there was no significant migration of pink-collar jobs to outer cities during the same period, and therefore the inner-to-outer district commuting behavior of pink-collar workers is not affected by their age. Figure 6.3(g) shows that the effect of age on cross-district commuting change with *hukou*. Before the age of 50, locals are more likely than migrants to commute from the inner districts to the outer districts. This is due to the fact that most of the migrants in this age group are renters (86.62%) and often choose to rent in the inner districts because of their jobs, while most of the locals are homeowners (86.76%), which makes it more difficult for them to move due to changes in their jobs. For people over the age of 50, combined with Figures 6.3(i) and 6.3(j), it can be seen that as members of the extended family, they are likely to rent a house in the inner districts with other young members of the family (their work is in the inner districts), thus making concessions in commuting. Figure 6.3(h) shows that the effect of *hukou* differs in terms of blue-collar workers. Blue-collar locals are more likely to commute from the inner districts to the outer districts with the suburbanization of the industry, in a similar explanation.

6.5 Conclusions

This paper analyzes the differences in residential location choices and cross-district commuting between different socioeconomic groups from the perspective of suburbanization and life cycle. Although Xiamen's outer city is not strictly a suburb, we consider it as a suburban and the inner districts as an inner-city for analysis and explanation because it has many suburban characteristics. To understand their interactions, a 2-step model was used to examine the residential choice (step 1) and the cross-district commuting behavior (step 2). Through this approach, the determinants and underlying mechanism of a spatial mismatch for different socioeconomic groups were estimated.

The results show that suburbanization, especially the continued suburbanization of blue-collar jobs in the last 20 to 30 years, has different effects on the housing choice and commuting of people of different ages, *hukou*, and occupations. The continued suburbanization of the industry attracted substantial numbers of young blue-collar workers to live in the outer districts. On the contrary, the abundant job opportunities in the inner city made young pink-collar and white-collar workers tend to live in the inner districts. As a result, young blue-collar workers are less likely than young pink- and white-collar workers to commute to the inner districts. Industrial suburbanization not only attracted large numbers of people but also prompted some of the original farmers (often with extended family structures) to engage in emerging non-agricultural industries in the outer districts. In addition, older residents are more likely than younger residents to buy and live in the outer districts due to lifecycle effects and housing affordability (Bayoh et al., 2006). Therefore, the probability of multi-worker households living in the outer districts increases with age. The phenomenon is more pronounced among migrants, especially white-collar migrants, and therefore they are more likely to commute to the inner districts than the locals as the age increases.

Meanwhile, the deindustrialization in the inner city affected the commuting behavior of the inner-city residents of different ages, *hukou*, and occupations. The continuous relocation of the manufacturing industry has created a spatial mismatch for the inner-district blue-collar workers, especially local ones. Therefore, the probability of blue-collar workers commuting to the outer district increases with age. The results also showed that there are significant differences in the migrants of inner and outer districts. Different from the outer-district migrants, the older migrants from a multi-worker household in the inner districts make a degree of compromise in commuting to accompany the younger generation. These results confirm that the inconsistencies in residence choices of different socioeconomic groups are caused by different mechanisms, which in turn lead to different commuting patterns.

This result provides the foundation for predicting the future development of the city, in particular the future development under the continuous urban renewal of the inner districts and the continuous development of the outer districts. To accelerate the construction of the Western Taiwan Straits Economic Zone (or West Coast Economic Zone), the Xiamen government is committed to developing a "cross-strait financial center" in the eastern part of Xiamen Island, which will result in the demolition of urban villages and the replacement of low value-added industries with high value-added ones. This would, on the one hand, force lower-income migrants to move to the outer districts and, on the other hand, generate cross-district commuting for high-skilled workers, especially those homeowners that are affected by the life cycle. With respect to policy implications, the results suggest that the potential spatial mismatch should be alleviated in two ways. First, efficient cross-district public transportation should be built to connect the inner districts and the outer districts for those who live in the latter and have to commute to the former. Second, the demolition of urban villages should be compensated for by affordable social housing for the benefit of migrants in the inner districts.

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7. Conclusions

7.1 Introduction

Economic development and housing reform have resulted in urban restructuring and exacerbated socio-spatial inequalities (Wang and Murie, 2000). Meanwhile, the disintegration of the *danwei* system has led to changes in the accessibility of jobs and amenities and further increased travel distances (Deng *et al.*, 2000). Jobs, housing, and amenities under the *danwei* system were provided as full packages and all activities could be done within the walls of the *danwei* community (Li and Kleiner, 2001). After the disintegration of the *danwei* system, housings and public services were no longer provided by the *danwei*, which then lead to the separation of workplace, amenities, and residence (Chai *et al.*, 2011). On the one hand, the separation of workplace and residence has prompted spatial mismatch problems. As housing was no longer provided by *danwei*, individuals had to seek housing independently. As a result, the geographical accessibility to jobs has become more and more important. On the other hand, after the limits of the *danwei* walls fell apart, residents were gradually attracted by external community service facilities, resulting in an increasing significance of higher-level public services. As Wang and Murie (2000) predicted, the past system and the development of market processes coexist in today's cities. This is because the process of marketization has produced patterns similar to that of Western cities, and the complete elimination of the legacy of the past residential model still needs more time (Wang and Murie, 2000). With the flow of migration, society has also become more heterogeneous. In that, socio-spatial inequalities increased, since different socioeconomic groups have unequal access to jobs and housing. Will these market-oriented changes lead to the same or different spatial patterns as can be found in Western countries, given the different starting points of spatial and social segregation? In that regard, one can ask himself the question in what sense do distinctive socioeconomic groups differ in their accessibility to jobs, housing, and public facilities? These questions are still not well answered for present-day Chinese society. As a consequence, there is a need for in-depth research that combines the mentioned contextual factors with individual attributes to arrive at a better explanation of the changing accessibility in China. To investigate the changing context and its impact on the accessibility to jobs, housing, and public facilities for distinctive socioeconomic groups in the city. This research takes Xiamen city, one of China's special economic zones, as the case study. Xiamen opened to the outside world earlier, and to a certain extent formed a spatial pattern similar to that of Western countries. As in the United States, manufacturing jobs in inner cities have been moved out to the suburbs and replaced by high-level jobs such as finance and business services (Liu et al., 2017; Michaels et al., 2019). Meanwhile, Xiamen has been free from the shackles of the traditional *danwei* system over the past 30 years. In 2015, only about 1% of households in Xiamen lived in the *danwei* housings (Xiamen Urban Planning and Design Institute, 2015). This makes Xiamen a good case for studying the spatial structure of Chinese cities since the market-oriented transformation, which not only increases the comparability with western countries but also provides a basis for predicting the future development of other cities in China to a certain extent.

7.2 Answers to the research questions

Our aim is to understand the extent to which the geographical distribution of housing, jobs and services, and the transportation system in Xiamen China affect the accessibility to work and amenities of different socioeconomic groups in Xiamen, China. Understanding these can provide scientific evidence and planning guidance for reducing the spatial inequality of public service facilities and alleviating the spatial mismatch problem. Starting with the identification of housing price mechanisms, the accessibility within the urban context (including the accessibility of jobs, public services, and public transport) and the accessibility at the individual level (commuting distance, commuting time, and residential location choice) are discussed. To achieve this goal, five research questions are proposed in Chapter 1, and the answers to each are discussed below.

1. To what extent do jobs, services, and transportation influence market prices in the rental and owner-occupied housing markets?

Chapter 2 investigates the determinants of market prices in four distinctive housing submarkets, including the owner-occupied and rental market in the inner districts and in the outer districts. Results from the hedonic price model demonstrate that there are similarities and differences in determinants of market prices between housing submarkets. Throughout the city, blue-collar jobs appear to lower housing prices and rents because of pollution and noise, while low-skilled pink-collar jobs have no statistically significant impact on housing prices and rents. Submarkets differ in some respects. The first difference can be found between the owner-occupied and the rental housing markets. Determinants like transaction time, school district, urban villages, various amenities, and public transportation show to have a much bigger influence on the owner-occupied markets than on the rental markets. Compared with renters, homeowners compete for more educational resources and better surrounding environments (Zheng *et al.*, 2016). The second difference can be found between the inner-district and the outer-district markets. These differences are mainly caused by the spatial, economic, and historical differences between these areas. The inner districts, as the commercial, cultural, historical and geographic heart of Xiamen, locate high-quality jobs and urban services that the outer district lacks. Accordingly, some problems caused by high-density development mainly appear in the inner districts. For instance, the negative impacts caused by hospitals, such as traffic congestion, noise, and air pollution, mainly appear in high-density inner districts rather than low-density outer districts. In addition, the positive effects of high-quality white-collar jobs and subsequently higher housing prices is mainly reflected in the inner districts rather than in the outer districts. On the one hand, this is because white-collar jobs with high added value are clustered in the inner districts, while small-scale white-collar jobs with relatively low added value are clustered in the outer districts. On the other hand, the urban living environment of the old city in the inner districts—where most white-collar jobs are located—has been significantly optimized by urban renewal, while the older parts of the city in the outer districts still face dilapidated living conditions. Moreover, since high-quality services are mainly concentrated in the inner districts, an efficient transportation system—BRT—has a more obvious positive effect on the housing prices and rents over there than in the outer districts.

2. To what extent does the accessibility of urban public facilities correspond to the needs of distinctive socioeconomic groups of residents?

Chapter 3 analyses the disintegrated and integrated accessibility of various public facilities by walking, public transportation, and private car. We were particularly interested in the accessibility of community- and district-level public facilities and the resulting degree of horizontal and vertical equity. To this end, we connected different levels of public facilities to distinctive modes of transportation, that is, community-level public facilities to walking, and district-level public facilities to public transportation and private car use. The methodology entails combining open data and travel survey data to analyze the accessibility of public facilities for different socioeconomic groups. Horizontal equity is related to "the distribution of impacts between individuals and groups considered equal in ability and need" (Litman, 2002, p. 3). Equal groups should "receive equal shares of resources," meaning that "public policies should avoid favoring one individual or group over others" (Litman, 2002, p. 3). In contrast, vertical equity is related to "the distribution of impacts between individuals and groups that differ in abilities and needs," and transport policies are equitable "if they favor economically and socially disadvantaged groups, therefore compensating for overall inequities" (Litman, 2002, p. 3). A factor analysis method is used to integrate socio-demographic variables and mobility needs and ability into a small number of factors. In general, the degree of vertical inequality is generally higher than that of horizontal inequality, indicating that disadvantaged groups experience a greater level of inequity. In particular, disadvantaged groups living in outer areas without access to vehicles experience the greatest inequities.

3. To what extent do distinctive socioeconomic groups differ in terms of the degree of spatial mismatch?

Chapter 4 analyses the job accessibility by public transportation and walking for different socioeconomic groups. Job accessibility has been calculated for three types of local and migrant workers in Xiamen city: blue-, pink-, and white-collar workers. The findings show that different spatial patterns and levels of job accessibility exist between locals and migrants, in particular for blue-collar workers and pink-collar workers. In general, it shows that the level of spatial mismatch is more substantial for blue-collar and pink-collar locals than for blue-collar and pink-collar migrants. Most blue-collar locals live in the outer districts, in particular on the urban fringe, mainly because of their peasant background. The spatial residential pattern of pink-collar locals is relatively dispersed, with half of them distributed in the inner districts and half in the outer districts. In contrast, migrant workers, both blue-collar and pink-collar, quite often rent a room or apartment in the urban villages or near their workplace; renters are far more flexible than homeowners in terms of residential mobility. For white-collar jobs and workers, there are differences between locals (more evenly dispersed) and migrants (more concentrated) in their residential distribution. The spatial distribution of the degree of spatial mismatch shows that white-collar local workers suffer more severe spatial mismatch than white-collar migrant workers. In general, although local workers face a higher degree of spatial mismatch, their commuting time (especially pink-collar and white-collar workers) are shorter than those of migrant counterparts. This is due to the different modes of transportation between local and migrant workers. The proportion of local workers commuting by private cars is higher than that of migrant workers, which reduces their commuting time to a certain extent.

4. To what extent do distinctive socioeconomic groups differ in their actual commuting behavior?

Based on the 2015 Xiamen household travel survey, this study examines commuting distance and commuting time for different occupational types of local and migrant workers, in particular blue-collar, pink-collar, and white-collar workers. One first finding is that these distinctive categories differ substantially in their commuting distances to jobs. The descriptive statistics show that migrant workers enjoy higher job accessibility and shorter commuting time than local workers, which is in line with the results in Chapter 3. This indicates that migrant workers have locational advantages in the sense of living closer to their work and possess a much lower degree of spatial mismatch than local workers. One underlying reason is that the majority of locals are homeowners (90%), while the majority of migrants (more than 80%) are renters, who are much more flexible than locals in the residential location choice. In the category of locals, blue-collar local workers commute over longer distances than white-collar local workers due to the bigger spatial mismatch of blue-collar local workers. Industrial relocation (suburbanization) after the 2000s and the rise of local peasant-workers living in peripheral cities have resulted in a spatial mismatch of blue-collar local workers, leading to the longest commuting distance and time for them. Due to the income restrictions, pink-collar local workers tend to choose public transportation instead of private cars and therefore commute more time but less distance than white-collar workers. In the category of migrants, blue- and pink-collar workers commute over shorter distances and time than white-collar workers. This may be due to the fact that white-collar jobs are more specialized and concentrated, and white-collar migrants can afford to pay the associated higher travel costs (Sermons and Koppelman, 2001). In general, living in an urban village will increase the commuting time of migrants. As most of the migrants living in urban villages are vulnerable groups, they tend to be at a disadvantage in terms of transportation, and their commuting time is longer than that of migrants living in other places.

5. To what extent is there a divergence in residential location choice and cross-district commuting among distinctive socioeconomic groups?

Chapter 6 analyzes the differences between residents of different ages, *hukou*, and occupations in their residential location choice and resulting long-distance commuting behavior. Therein, once again a distinction is made in three distinctive occupations (blue-collar, pink-collar, white-collar). In order to understand their interactions, a 2-step model was developed, which examined the residential choice in the first step, and the long-distance commuting behavior in the second step. The results show that the continued suburbanization of blue-collar jobs in the past 30 years has different effects on the housing choice and commuting of residents of different ages, *hukou*, and occupations. The continued suburbanization of the industry attracts substantial numbers of young blue-collar workers to live in the outer districts, while the abundant job opportunities in the inner city attract young pink-collar and white-collar workers to live in the inner districts. Consequently, outer-district young blue-collar workers are less likely than young pink- and white-collar workers to commute to the inner districts. The probability of multi-worker households living in the outer districts increases with age due to the lifecycle effects and housing affordability (Bayoh *et al.*, 2006). This phenomenon is more pronounced among migrant households, especially white-collar migrants, who are more likely than locals to commute to the inner districts with increasing age. Concurrently, inner-city deindustrialization affects the commuting behavior of the inner-city residents of different ages, *hukou*, and occupations. The development of large industrial zones and Taiwan investment zones in the outer districts resulted in a certain degree of spatial mismatch between jobs and housing for blue-collar and white-collar workers in the inner districts. As a result, the older the blue-collar and white-collar workers are, the more likely they are to commute from the inner districts to the outer districts. In contrast, given the fact that there was not a large moving out of pink-collar jobs from inner-city to outer-city during the same period, the inner-to-outer district commuting behavior of pink-collar workers is not affected by their age. Furthermore, migrants are less likely to commute from the inner districts to the outer districts since they choose to live close to their jobs. These results confirm that the differences in the residential choice of different socioeconomic groups are caused by different mechanisms, which in turn lead to different commuting patterns.

7.3 Theoretical implications

7.3.1 Potential accessibility: The influence of land use, transportation, and personal constraints

Since the home is the place that generates the greatest number of trips (Golledge, 1997), residential location is crucial in accessing jobs and public services. The residential choice is influenced by macro-level factors (land use component and transportation component) and micro-level factors (individual component). Our study shows that there are differences in housing ownership between migrants and locals. Almost 90% of locals appear to be homeowners, while less than 20% of migrants appear to be homeowners (Chapter 5). As the residential choice of distinctive socioeconomic groups leads to divergent commuting behavior, exploring the pricing mechanisms of different housing markets can help to understand the deeper causes of travel behavior of distinctive socioeconomic groups, in particular with respect to the different housing submarkets (inner districts owner-occupied housing, outer districts owner-occupied housing, inner districts rental housing, and outer districts rental housing). However, previous studies have limited themselves foremost to the owner-occupied housing market, and in that neglected the rental housing market (Hu *et al.*, 2014; Wen *et al.*, 2014; Li *et al.*, 2016; Liu *et al.*, 2017). This is due in part to the neglect of housing problems of the category of migrants and in part to the unavailability of rental housing data. With the new emerging open data, we found that the owner-occupied housing market and rental market differ substantially in their determinants (Chapter 2).

The existing spatial organization can be traced back to the disintegration of the *danwei* system, the housing reform, and the overall suburbanization, which reorganized the spatial pattern at both the community and the urban level, and as a consequence changed the individual's activity space (Chai et al., 2011). Our study confirms that the spatial reorganization caused by the above-mentioned developments further marginalized weaker socioeconomic groups through processes such as urban segregation and institutional discrimination. In terms of access to public facilities, the vertical equity index indicates that the disadvantaged groups have higher levels of inequality (Chapter 3). In terms of job accessibility and spatial mismatch, blue- and pink-collar migrants generally experience a lower degree of spatial mismatch than blue- and pink-collar locals (Chapter 4). Ostensibly, this result indicates that with regard to spatial mismatch, the migrant workers are in an advantageous position compared with the local workers. However, the essence of this phenomenon is that migrants are forced to choose the rental market, especially the rental housing in urban villages, because they are almost unable to enter the owner-occupied housing market, leading to a certain degree of residential segregation. With the continuous demolition of urban villages caused by urban renewal, their advantages in spatial mismatch will eventually disappear.

7.3.2 Actual accessibility: The influence of spatial mismatch and personal constraints

The exploration of the divergence in spatial mismatch and commuting behavior between locals and migrants and between blue-collar, pink-collar, and white-collar workers is another major theoretical contribution of this study in comparison to previous studies that generally ignores the differences in commuting distance for these distinctive types of workers. The findings show that the six distinguished socioeconomic groups are different in their residential choice, in their level of job accessibility, and in their actual travel behavior (Chapter 4). The detected divergence in the spatial mismatch between distinctive socioeconomic groups results in divergence in commuting behavior for those groups (Chapter 5). In general, migrant workers commute over shorter distances than local workers. Although white-collar migrants and white-collar locals possess higher overall job accessibility than blue- and pink-collar workers, they commute longer distances as their jobs are more specialized and concentrated.

Our results confirm that housing and economic reforms have marginalized weaker socioeconomic groups through processes such as urban segregation and institutional discrimination. Although migrants have an advantage over the locals in terms of commuting distance, these advantages are eliminated because of their disadvantages in transportation. In addition, their advantage in the commuting distance is due to the high price of housing that prevents them from entering the owner-occupied housing market, which further exacerbates the residential segregation. Our results also show that cities like Xiamen, which entered the marketization process in the early stage and no longer had many *danwei* left, also formed a different social-spatial pattern from that found in Western countries, especially the United States. This is partly due to the difference in suburbanization between China and the United States. The large-scale suburbanization in the United States in the 20th century was the result of residents' active choice to escape the crowded and noisy living environment and crime in the central city. The driving force of suburbanization in the United States is the American middle class, whose preference for larger single-family plots in the suburbs was reinforced by transportation innovations (Mieszkowski and Mills, 1993). In this context, the left behind in the inner city of low-income blue-collar workers and the suburbanized manufacturing industry have caused a spatial mismatch (Kain, 1968). In contrast, the suburbanization initiated in China after the 1980s is the result of residents' passive choice to escape the high housing price in the inner city. The subjects of suburbanization in China can be categorized into three groups: the first group is the small number of wealthy people who did buy themselves suburban villas; the second group is the group of employees of the relocated enterprises and the indigenous people who were resettled to the suburban areas after urban redevelopment; and the third group is the group of home buyers attracted by low suburban housing prices. The suburbanization of manufacturing industry and the suburbanization of corresponding blue-collar workers belong to the second group. Although a small number of blue-collar workers, particularly local workers, still reside in the inner districts and in that generate the inner to outer districts commuting flow, most blue-collar workers settle in the outer districts, and as a consequence no large-scale spatial mismatch emerged like in the United States.

7.4 Methodological implications

7.4.1 Transformations of urban studies in the big/open data era

One methodological contribution of our study concerns the use made of free and open data. With the emergence of big/open data in recent years, many changes have taken place in urban studies (Long and Liu, 2016). Previously, researchers collected data themselves, or received data through personal relationships from relevant government departments, or bought datasets from traditional data-oriented companies making research much more expensive. Recently, national, regional, and local governments begin to release some data in open formats to improve transparency. Many of the economic transactions that used to be done offline have been moved now online, and their archives serve as a "side effect" by creating vast amounts of data reflecting many aspects of human behavior (Arribas-Bel, 2014). In many cases, the data is also available to the public, creating many research opportunities for researchers. The housing market, for example, has undergone a revolution in recent years that have greatly improved the availability of online databases. A website like https://xm.lianjia.com/ which is applied in Chapter 2 provides a large overview of the housing markets as well as housing transaction records. These data are usually freely available via websites, and researchers can extract the data according to their research needs. In addition to the data cost advantage, this website has two other advantages. First, the nested map which shows the exact location of the housing enables researchers to extract latitude and longitude data through the web crawler technology, which will reduce location measurement errors of observations (Arribas-Bel, 2014). Previously, locational data was released in the form of addresses, which needed additional processing of inputting data into a GIS. In some cases, the imperfect address did make it difficult to digitalize. As this process requires a considerable amount of work, most researchers outsourced these tasks (Overman, 2010). Opposite to address data, digital geocoded data including latitude and longitude can be converted directly to point data in a GIS, significantly reducing efforts and costs. In addition, as most of the housing data are limited to sales records, previous research has focused on the sales market, and in that neglected the rental market. The rental housing transaction records released in https://xm.lianjia.com/ did enable us to conduct extensive research on rental prices. Moreover, free access to housing transaction records represents a tremendous opportunity that formerly used to be restricted to just a few researchers, and we can now even extend our research to cross-regional study in the future. The spatial, as well as temporal availability of these sources of data, is diverse, and in some cases, the data can be obtained in “real-time”. To conclude, new emerging data and their open availability to researchers have reduced research costs and exclusive deals with the company/institution (Arribas-Bel, 2014). Moreover, additional data that was not collected in a traditional way and spatial-temporal data enables us to extend our knowledge in the different fields of urban analysis and to improve the efficiency and accuracy of the research.

7.4.2 Accessibility measurements in the new era

The spatial, as well as temporal availability of these sources of data, is diverse, and in some cases, real-time data or data for a specific timeframe can be obtained. These opportunities have great advantages in the study of multiple data sources. When using two sets of traditional data, researchers usually encountered considerable time differences between the two datasets. For example, when the 2010 census data (ten years in the case of most censuses in the US) and the 2019 questionnaire survey data were used in one research, the results of the analysis may be biased by changes in the macro environment of the two datasets. In contrast, big data allows us to obtain data that is consistent in its time component in relation to another set of data since the large volume generated by these sources—which can be understood as a real-time data stream—provide data at any time. In chapters 3 and 4, we obtained a travel time matrix from Gaode API at 8:00 am on June 15, 2015, which is consistent with the date of the Xiamen household travel survey. Different from GIS-based network analysis which inaccurately preset road conditions, Gaode API calculates travel time according to the actual traffic situation. In addition, the data provided from Gaode API enables us to measure accessibility by public transportation more precisely. Previous studies on accessibility measurements by public transportation oversimplified and overrated its efficiency by ignoring the factual bus routes and factual bus stops (Grengs, 2012; Mao and Nekorchuk, 2013). Using Python programming language, travel distance and travel time between each unit can be computed according to the actual route and the actual time spent on the bus route (including walking from origin to bus stop, distance and time for public transit, transfer time and distance, walking to destination). As a result, API based accessibility measurements provide a more accurate calculation than single GIS-based measurements. Despite these advantages, map-based open data still has some deficiencies of its own. Although those data enable us to combine land use components and transportation components when measuring accessibility, it still lacks socioeconomic information. Moreover, it only explores the space-time relationship between locations, but fail to examine the actual behavior of the subject. In order to fill this gap, this dissertation combines emerging open and big datasets with collected travel survey data which contains actual travel behavior of individuals and their socioeconomic attributes to measure potential and actual accessibility.

7.5 Policy implications

7.5.1 “Transit metropolis” and transit-oriented development.

In his classic book, Cervero (1998) was the first to define the “transit metropolis” as “a region where a workable fit exists between transit service and urban form”. In recent years, the Chinese government has implemented various policies to promote the “transit metropolis” construction, all with the goal of reducing automobile dependency, improving the efficiency of public transportation operation, and alleviating urban traffic congestion. In addition, the “Evaluation index system of transit metropolis” which was issued in 2013, has presented the main index of "Transit metropolis" construction in China. According to this index, for the “transit metropolis” with rail transit and without rail transit, the share of public transportation in the modal split should account for more than 45% and 40%, respectively. Although Xiamen did strive to build a “Transit metropolis”, it failed to be selected as an official “Transit metropolis” demonstration City in 2012. In fact, Xiamen is getting farther away from her goal to reach this status. Between 2009 and 2015, the share of public transportation in the modal split dropped from 31% to 25.7%, while the proportion for private cars increased from 8.21% to 17.8% in this period. This trend will threaten the forthcoming of a “transit metropolis” since growing reliance on the private car will reduce the demand for public transportation which in turn will increase the cost of bus operation. One way to develop a transit metropolis is by implementing the concept of transit-oriented development (TOD). In this regard, governmental documents have made clear that the essence of national "transit metropolis" construction is TOD. With TOD, it is intended to increase public transportation ridership by promoting dense, mixed land-use and compact urban form within a walking distance of transit station (Vale, 2015). It is a walkable community that integrates housing, employment, and public facilities (Loo and du Verle, 2017). Since the opening of the first line on December 31, 2017, Xiamen Metro currently has two lines in operation and four lines under construction. These lines connect six administrative districts and play a key role in building the TOD communities.

To create attractive TOD communities to improve living capacity, quality of life, social equity, and reduce car dependency, corresponding policies and measures need to be designed and adopted. First, TOD communities in the outer districts need to achieve a certain degree of job-housing balance. Due to the limited land resources available in the inner districts, the current new housing market is mainly developed in the outer districts (Chapter 2). However, the city's employment, in terms of pink- and white-collar jobs, is concentrated foremost in the inner districts (Chapter 4). Ignoring the development of new pink- and white-collar jobs in the outer districts will generate a large volume of commuting flows between the inner and outer districts. Second, public facilities at the city-, district-, or sub-district level should be located within the TOD communities. The efficiency of the public transportation system has a significant impact on the accessibility of district-level public facilities (Chapter 3). Therefore, allocating such facilities in these areas can improve the overall accessibility level. Third, TOD communities should build a certain proportion of government-subsidized owner-occupied housing and government-subsidized rented housing. For relatively low-income groups, it is difficult to compete for the TOD community, since high accessibility to jobs, urban amenities, and metro stations will increase the housing prices (Chapter 2). Low-income groups tend to rely more on public transportation than high-income groups, and therefore government-subsidized owner-occupied housing and government-subsidized rented housing in TOD communities will undoubtedly improve their degree of accessibility.

7.5.2 Housing guarantee for potential displaced migrants

The bid rent theory states that different land users will compete for land close to the city center (Alonso, 1964). Old manufacturing industries in the inner city could no longer afford high land prices and have been substituted by high-level jobs while being suburbanized. Meanwhile, as the benefits of redevelopment outweigh the costs, the original low-density or low-floor housing in the inner city has become the new market of real estate developers. In general, there are two groups of residents living in the so-called urban villages or ViCs: the villagers who own the homes over there and who rent these out to migrants; and the migrants who rent rooms in the homes of villagers (Chapter 5). Since most compensation is received by the homeowners, the villagers in the urban villages are eager to redevelop, while the renters face the fate of being expelled. As one of the "Western Taiwan Straits Economic Zones", its special geographical location enables the eastern coastal area of Xiamen planned to be the Cross-strait financial center. Therefore, large numbers of urban villages in the Huli district are facing demolition and those demolished urban villages will be replaced by high rise buildings for high-income groups. Currently in Xiamen, the municipal government has started to combine the redevelopment of urban villages with the provision of resettlement housing within 5km from the original sites. As a consequence, the residents with local *hukou* can reside in almost the original site while the migrants without local *hukou* are facing eviction. It is undeniable that urban villages, especially urban villages in the inner city, play an important role in accommodating the migrants and in reducing housing and commuting costs (Chapter 4, 5, and 6). Therefore, the demolition of urban villages will displace these migrants to the suburbs or even to other cities and cause the spatial mismatch of these migrants, especially pink-collar migrants—who are urgently needed in the shops and restaurants in the city center. To improve the urban absorptive capacity for potential evicted migrants, especially pink-collar migrants, corresponding policies and actions should be taken. First, the supply channels of rental housing should be expanded. Our research shows that migrants mainly enter the rental market, especially the low-rent market (Chapter 5, and 6). It implies that the reduction of low-priced rental housings caused by the demolition of urban villages should be compensated by the supply of low-priced rental housings in the vicinity. In this regard, the "Opinions of the six departments on rectifying and regulating the order of the housing rental market" and other policies that allow vacant commercial office buildings, industrial plants, and other non-residential buildings to be converted into rental housing, will be possibly a beneficial strategy (State Administration for Market Regulation *et al.*, 2019). In order to stabilize the supply of pink-collar labor in the inner districts and ensure their settlement over there, it is necessary to adopt the aforementioned policies to provide cheap rental housing. Second, the government should vigorously monetize public rental housing and include the low-income migrants in the housing guarantee system. Although many relevant policies make it clear that migrant workers with stable employment in urban areas should be included in the coverage of public rental housing (Instrumentalities of the State Council and General Office of the State Council, 2016), the proportion of migrant workers who successfully apply for public rental housing is extremely small, especially for low-income migrant workers. In the sustainable and harmonious development of cities, the supply of low-skilled service labor force is essential. In order to meet the indispensable service labor force in cities, it is important to extend the coverage of social housing monetization to meet the housing needs of these migrants.

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Summary

The economic reform in the early eighties of the previous century was the starting point for the massive urbanization in China. Economic development and housing reform resulted in urban restructuring and the influx of large numbers of migrant populations. Distinct socioeconomic groups have shaped different urban living spaces through residential agglomeration, integration, and isolation, and their spatial connections with employment and public services are also diverse. However, there is still insufficient evidence to show whether housing and economic reforms have further marginalized weaker socioeconomic groups through processes such as urban segregation and institutional discrimination. The soaring housing prices after the housing reform have prompted differences in location choices and housing property (e.g. rental or owner-occupied housing) for different socioeconomic groups. The divergent housing selection further leads to differences in their accessibility to public services and jobs, which may ultimately aggravate socioeconomic inequalities. It is necessary to study the spatial differences of distinctive groups in housing, employment, and public services to better understand the inequity issues.

Through in-depth empirical analysis, this study aims to understand the differences in the spatial relationships of employment, housing, and public services among different socioeconomic groups and the resulting socioeconomic inequalities. The datasets used in this research include four main resources: housing sales and rental data, Points of Interest (POI) data, employment data, and 2015 Xiamen household travel survey data.

Our study confirms that the spatial reorganization caused by housing and economic reforms further marginalized weaker socioeconomic groups. This is primarily reflected in their choice of housing location and tenure types. This research investigates the determinants of the four housing submarkets classified by owner-occupied and rental housing in the inner and outer districts to unravel the heterogeneity of housing choices among different socioeconomic groups. Our results show that the majority of the local population are homeowners, while the majority of the migrant population are renters. For the local population, restricted by housing prices, low-income groups are in a disadvantaged position when competing for educational resources and the surrounding environment. For the migrant population, the amount of rent and proximity to work are the most important factors in their housing choice, and the accessibility of public service facilities around the housing has no obvious impact on the rental market than on the owner-occupied market. As pollution and noise associated with blue-collar jobs reduce housing rents, the migrant population tends to gather around blue-collar jobs to reduce their housing expenses.

On the one hand, disparities in housing choices among distinct socioeconomic groups lead to different degrees of accessibility to public services. Regardless of the inner city and outer city, areas with a high proportion of migrant renters who do not own cars tend to have lower accessibility to public services than those with a lower proportion of such groups.

Similarly, areas with a high proportion of local populations with low education and poor skills tend to have less access to public services than those with a low proportion of such groups, which is mainly reflected in outer cities. These results indicate that disadvantaged groups experience a greater level of inequity. In particular, disadvantaged groups living in outer areas without access to vehicles experience the greatest inequities.

On the other hand, differences in the spatial distribution of employment and residence among distinct socioeconomic groups result in varying degrees of job accessibility and spatial mismatch. In general, it shows that the level of spatial mismatch is more substantial for blue-collar and pink-collar locals than for respectively blue-collar and pink-collar migrants. This is mainly because migrant workers, who often rent a room or apartment in an urban village, are much more flexible than homeowners and can easily adjust their living place to accommodate changes in the working place. However, it is found that despite the large spatial mismatch, the commuting time of local workers is shorter than that of migrant workers due to the differences in travel modes. These results show that the spatial relationship between employment and residence alone cannot fully reflect the difficulty of different groups in actual travel activities, and the differences in their travel modes must be considered.

In addition to potential job accessibility and public service accessibility, this study also investigates actual commuting activities at the individual level. The micro-level analysis shows that the commuting distance of migrant workers is shorter than that of local workers, which is consistent with the results of other cities in China, and once again confirms that the migrant workers experience a lower level of spatial mismatch than the local workers. This research extends the current comparative study of commuting patterns of local and non-local workers by distinguishing their occupations and confirms that there is considerable heterogeneity in commuting time and distance between different types of workers. This is due to the spatial differences between each industry, which will further lead to inconsistencies in the commuting patterns of workers with different occupations. Our results show that the commuting time of migrant renters living in other areas is shorter than the commuting time of migrants living in urban villages, indicating that the migrant renters living in urban villages are in a disadvantaged position in terms of commuting time.

In the context of China, this study delivers two policy implications. On the one hand, newly built areas should maximize the provision of housing, jobs, and public services within walking distance of transit stations. First, this research reveals the imbalance in the distribution of white-collar jobs and pink-collar jobs in the outer and inner districts. Therefore, to avoid a large amount of outer-to-inner district commuting flow, TOD communities in the outer districts need to achieve a certain degree of job-housing balance and ensure the supply of white-collar and pink-collar jobs. Second, this research confirms the substantial difference in the accessibility of public service facilities between the outer and inner districts and between disadvantaged and advantaged groups. Thus, public facilities at the city-, district-, or sub-district level should be allocated within the TOD communities to improve the overall accessibility level. Third, this research reveals the importance of public transportation for low-income locals and migrant renters. Accordingly, TOD communities should provide a certain proportion of government-subsidized owner-occupied housing and government-subsidized rented housing.

On the other hand, the study calls for extending the coverage of low-rent housing to the migrant population. Urban villages play an important role in accommodating migrants and reducing housing and commuting costs, thereby the demolition of urban villages will divert these migrants to suburbs and even other cities. To improve the urban absorptive capacity for potential evicted migrants, the government should first expand the supply of rental housing. In this regard, allowing vacant commercial office buildings, industrial plants, and other non-residential buildings to be converted into rental housing may be a beneficial strategy. Second, the government should extend the coverage of low-rent housing to the migrant population. In the sustainable and harmonious development of cities, the supply of a low-skilled service labor force is essential. To ensure the supply of indispensable service labor force in cities, it is necessary to extend the coverage of social housing to meet the housing needs of these migrants.

Samenvatting

De economische hervormingen aan het begin van de jaren tachtig van de vorige eeuw waren het startpunt voor de massale verstedelijking in China. Deze economische ontwikkelingen en de hervormingen op het vlak van huisvesting hebben geleid tot grootschalige herstructureringen en een toestroom van grote aantallen migranten. Agglomeratieprocessen, integratie en isolatie, hebben er vervolgens toe geleid dat er afzonderlijke leefgebieden zijn ontstaan voor bepaalde sociaal-economische groepen met een eigen toegang tot werkgelegenheid en publieke diensten. Vooralsnog ontbreekt het echter aan toereikend bewijs voor de stelling dat de hervormingen in huisvesting en economie hebben geleid tot een verdere marginalisering van zwakkere sociaal-economische groepen onder invloed van stedelijke segregatie en institutionele discriminatie. De stijgende huizenprijzen na de hervormingen hebben ertoe geleid dat onderscheiden sociaal-economische groepen verschillen in hun keuzes van woonlocatie en type van huisvesting (bijv. huur- of koopwoningen). De uiteenlopende keuzes leiden er verder toe dat de onderscheiden groepen verschillen in hun toegang tot publieke diensten en werkgelegenheid, hetgeen uiteindelijk de sociaal-economische ongelijkheid tussen deze groepen kan doen toenemen. Het is daarom van belang om de ruimtelijke verschillen tussen onderscheiden groepen in huisvesting, werkgelegenheid en publieke diensten nader te bestuderen om zo de ongelijkheden beter te kunnen begrijpen.

Deze studie beoogt door middel van empirisch onderzoek de verschillen in ruimtelijke relaties tussen werkgelegenheid, huisvesting en publieke diensten voor de onderscheiden sociaal-economische groepen te onderzoeken om zo de ongelijkheden tussen deze groepen beter te kunnen begrijpen. De datasets die in dit onderzoek worden gebruikt zijn vooral afkomstig van vier belangrijke bronnen: gegevens over de verkoop en verhuur van woningen, gegevens over belangrijke locaties (Points Of Interest), gegevens over werkgelegenheid en gegevens uit de Xiamen-enquête over reisgedrag van huishoudens in 2015.

Ons onderzoek toont aan dat de ruimtelijke reorganisatie onder invloed van de hervormingen in huisvesting en economie de positie van de zwakkere sociaal-economische groepen verder heeft gemarginaliseerd. Dit komt vooral tot uiting in hun keuze van de woonlocatie en het type van huisvesting. Om dit te onderzoeken heeft deze studie zich gericht op de determinanten van vier woningsubmarkten: koop- en huurwoningen, gelegen in de binnenstad en in de buitenwijken. De resultaten laten zien dat van de lokale bevolking de meerderheid behoort tot de klasse van huiseigenaren, terwijl daartegenover van de migranten de meerderheid behoort tot de klasse van huurders. Van de lokale bevolking bevinden de lagere inkomensgroepen zich onder invloed van de huizenprijzen in een achterstandspositie in hun competitie voor goed onderwijs en een aantrekkelijke

leefomgeving. Voor de migranten zijn de hoogte van de huur en de nabijheid van werk de belangrijkste factoren bij hun woonlocatie- en huisvestingskeuze. De bereikbaarheid van publieke voorzieningen in de omgeving van de woning blijkt daarentegen geen duidelijke impact te hebben op de huurmarkt noch op de koopmarkt. Omdat vervuiling en lawaai in de nabijheid van laagbetaalde werkgelegenheid de huurprijzen verlaagt, clusteren met name migranten zich rondom dergelijke concentratiepunten en weten zo hun huisvestingskosten te reduceren.

Enerzijds leiden verschillen in huisvestingskeuzes tussen onderscheiden sociaal-economische groepen tot verschillen in toegankelijkheid tot publieke diensten. Ongeacht binnenstad of buitenwijken, gebieden met een hoog aandeel migranten zonder eigen autobezit kennen doorgaans een lagere mate van toegankelijkheid tot publieke diensten dan gebieden met een lager aandeel van dergelijke groepen. Evenzo kennen gebieden met een hoog aandeel lokale bevolking met laag onderwijsniveau en gebrekkige vaardigheden doorgaans een mindere mate van toegangkelijkheid tot publieke diensten dan die met een laag aandeel van dergelijke groepen, wat vooral tot uiting komt in de buitenwijken. Deze resultaten tonen aan dat kansarme groepen een grotere mate van ongelijkheid ervaren. Met name achtergestelde groepen, woonachtig in buitenwijken en zonder toegang tot eigen gemotoriseerd vervoer, ondervinden de grootste mate van ongelijkheid.

Anderzijds leiden verschillen in de ruimtelijke spreiding van werk en wonen voor de onderscheiden sociaal-economische groepen tot verschillen in de mate van toegankelijkheid van werk en daarmee tot een ruimtelijke mismatch. In het algemeen blijkt de mate van ruimtelijke mismatch groter te zijn voor lokale handarbeiders en mensen werkzaam in de ondersteunende diensten dan voor migranten die tot die beroepsgroepen behoren. Dit komt vooral doordat arbeidsmigranten, die vaak een kamer of appartement huren in een zogeheten 'Urban Village', veel flexibeler zijn dan huiseigenaren en zodoende gemakkelijk hun woonplek kunnen aanpassen aan veranderingen in de werkplek. Desalniettemin blijkt dat ondanks een grotere ruimtelijke mismatch, de reistijd van lokale werknemers korter is dan die van migranten, met name als gevolg van verschillen in voor hen toegankelijke vervoerswijzen. Deze resultaten tonen aan dat enkel inzicht in de ruimtelijke relatie tussen wonen en werken niet voldoende is als uiting van het feitelijke reisgemak want dat daarvoor moeten ook de verschillen in mogelijkheden tot verplaatsing worden meegewogen.

Naast onderzoek naar de potentiële bereikbaarheid van banen en de toegankelijkheid van publieke diensten wordt in deze studie ook gekeken naar het daadwerkelijke woon-werkverkeer op individueel niveau. De analyse op microniveau toont aan dat de woon-werkafstand van migranten korter is dan die van lokale werknemers, hetgeen consistent is met de resultaten uit andere steden in China. Dit bevestigt nogmaals dat migranten een kleinere ruimtelijke mismatch kennen dan lokale werknemers. Daarnaast heeft dit onderzoek gekeken naar verschillen in pendelstromen tussen beroepsgroepen. Daaruit blijkt dat er aanzienlijke verschillen zijn in woon-werk pendeltijd en -afstand tussen verschillende soorten werknemers, hetgeen vooral samenhangt met ruimtelijke verschillen tussen bedrijfstakken. Onze resultaten laten zien dat de woon-werk reistijd van migrant-huurders die in 'Urban Villages' wonen langer is dan die van migranten die buiten de 'Urban Villages' wonen. Dit blijkt vooral te wijten te zijn aan verschillen in toegankelijkheid van vervoersmogelijkheden. Kortom, migranten woonachtig in 'Urban Villages' bevinden zich voor wat betreft hun woon-werk reistijd in een relatief ongunstige positie ten opzichte van migranten woonachtig buiten 'Urban Villages'.

Voorgaande uitkomsten leveren twee beleidsaanbevelingen op binnen de Chinese context. Enerzijds is het wenselijk dat in nieuwbouwgebieden het aanbod aan woningen, werkgelegenheid en publieke diensten op loopafstand van OV-stations wordt gemaximaliseerd. Ten eerste toont dit onderzoek de onevenwichtigheid aan in de verdeling van banen voor kantoorpersoneel en personen werkzaam in de ondersteunende dienstensector in de buitenwijken en het stadscentrum. Om te voorkomen dat er een grote pendel van woon-werkverkeer gaat ontstaan van de buitenwijken naar het stadscentrum, zouden TOD-gemeenschappen (Transit Oriented Development) in de buitenwijken een bepaalde mate van evenwicht moeten bereiken tussen werk en huisvesting en moet er worden gezorgd voor voldoende aanbod aan banen voor kantoorpersoneel en in de ondersteunende dienstensector. Ten tweede bevestigt dit onderzoek het grote verschil in toegankelijkheid van publieke voorzieningen tussen de buitenwijken en het stadscentrum en tussen kansarme en kansrijke bevolkingsgroepen. Daarom moeten publieke voorzieningen op het niveau van de stad, het district of het subdistrict worden toegewezen aan TOD-gemeenschappen om zo het algehele niveau van toegankelijkheid te verhogen. Ten derde toont dit onderzoek het belang aan van goed openbaar vervoer voor zowel lokale bewoners met een laag inkomen alsook voor migranten in de huursector. Daarom zouden TOD-gemeenschappen een bepaald aandeel door de overheid gesubsidieerde koop- en huurwoningen moeten aanbieden.

Aan de andere kant roept deze studie op om de doelgroep die toegang heeft tot goedkope huurwoningen uit te breiden tot de categorie van migranten. 'Urban Villages' spelen een belangrijke rol bij de huisvesting van migranten en het verminderen van kosten voor huisvesting en van woon-werkverkeer. De sloop van 'Urban Villages' zal ertoe leiden dat deze migranten verhuizen naar de buitenwijken of zelfs de stad zullen verlaten. Het is aldus noodzakelijk voor de locale overheid om de categorie van goedkope huurwoningen uit te breiden. In dit opzicht kan het een gunstige strategie zijn om leegstaande commerciële kantoorgebouwen, industriële installaties en andere utiliteitsgebouwen om te vormen tot huurwoningen. Ten tweede zou de overheid de toegangkelijkheid van goedkope huurwoningen kunnen uitbreiden tot de categorie van migranten. Voor een duurzame en harmonieuze ontwikkeling van steden is een toereikend aanbod van laaggeschoolde dienstverlenende arbeidskrachten essentieel. Om dit te waarborgen, is het noodzakelijk om voldoende sociale huisvesting te realiseren zodat aan de huisvestingsbehoeften van deze migrantenpopulatie kan worden voldaan.

Appendix

Appendix I: Sector-based job classifications and description

Code	Sector	No. of firms	No. of jobs	Low education		High education
				Blue-collar	Pink-collar	White-collar
A	Farming, forestry, animal husbandry, and fishery	804	10,811			
B	Mining	14	123	√		
C	Manufacturing	13,574	810,171	√		
D	Production and supply of electricity, gas, and water	46	3649	√		
E	Construction	2898	460,236	√		
F	Transportation, storage, and postal services	2421	77,636	√		
G	Information transmission, software, and information technology	2508	35,410			√
H	Wholesale and retail trades	25,843	262,558		√	
I	Hotels and catering services	1219	53,534		√	
J	Finance intermediation	414	17,961			√
K	Real estate	2607	61,701		√	
L	Leasing and business services	7999	82,716		√	
M	Scientific research and technical services	1792	27,437			√
N	Management of water conservancy, environment, and public establishments	294	8370		√	
O	Household services, repairs, and other services	1359	25,538		√	
P	Education	607	32,637			√
Q	Health and social services	111	11,825			√
R	Culture, sports, and entertainment	532	13,512			√
S	Public management, social security, and social organization	849	30,392			√

Note: Since the work location of the construction industry is often a construction site, rather than the location of a company, this study does not include the construction industry in blue-collar jobs

Appendix II: Occupation-based worker classifications and description

Description	Total sample size	No. of workers	Low education		High education
			Blue-collar	Pink-collar	White-collar
Unit heads	43,670	2725			√
Professional and technical personnel	43,670	8186			√
Clerks and related workers	43,670	9202			√
Business service personnel	43,670	14,653		√	
Agriculture and water conservancy laborers	43,670	2810			
Production, transportation equipment operators, and related workers	43,670	6094	√		

Appendix III. Modal split

	Locals			Migrants		
	Blue-collar worker	Pink-collar worker	White-collar worker	Blue-collar worker	Pink-collar worker	White-collar worker
Walking	9.0%	15.5%	13.8%	36.4%	29.8%	21.7%
Cycling	14.0%	13.3%	7.3%	21.2%	13.8%	11.9%
Bus	19.6%	28.8%	25.2%	26.6%	40.0%	37.1%
BRT	1.5%	3.0%	2.8%	1.5%	3.4%	2.7%
Motorcycle	33.2%	14.9%	11.1%	9.2%	3.3%	6.3%
Private car	22.7%	24.5%	39.8%	5.1%	9.6%	20.3%

Curriculum Vitae

Yongling Li was born in Shenyang, Liaoning, China, on 13 January 1988. She received her BSc in Urban Planning from Nanjing University in 2011. She continued her Master's studies in Urban Planning and Design in Xiamen University (2011-2014). From 2014 through 2021, she conducted her Ph.D. research on Accessibility and socio-spatial inequality between locals and migrants at the Department of Human Geography and Planning, Faculty of Geosciences, Utrecht University. She intends to become an independent scholar after the promotion.