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

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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.

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, we need to elaborate on 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 most rural migrants lack urban citizenship (*hukou*) and have involved in low-income jobs, most of them

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have limited access to commercial and affordable housing in the city. Consequently, 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.

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 and 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 (Fig. 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.

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 and 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 order 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, 2016, 2017; 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.

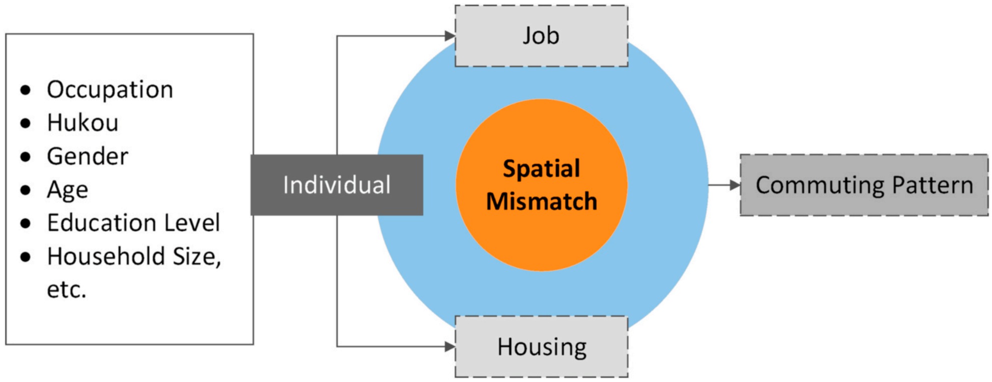

Fig. 1. The mechanisms of spatial mismatch.

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 and Niemeier, 1997). Several lines of evidence suggest that age is negatively related to trip distance (Mercado and 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.

3. Methodology

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 (Fig. 2). 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.

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-h) 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.

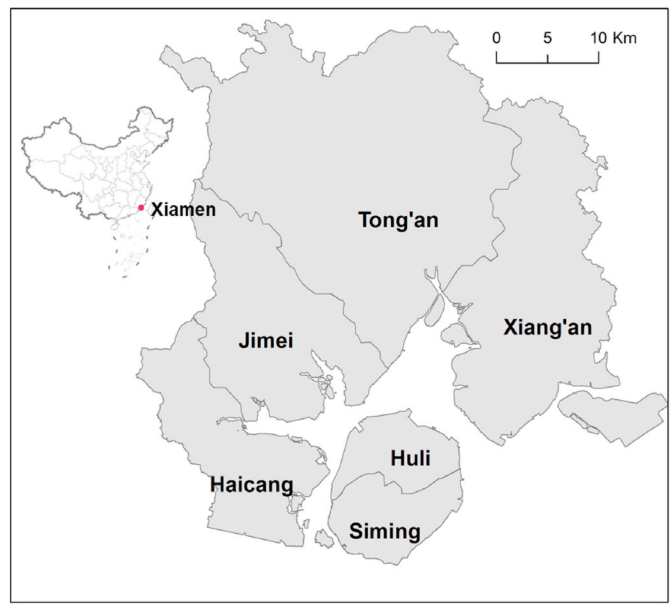

Fig. 2. Xiamen city in China: location and administrative divisions.

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 and Roo, 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:

$$D_i = \begin{cases} D_i^{'} & \text{if } D_i^{'} > 0 \\ T_i * S_j^{*} & \text{if } D_i^{'} = 0 \end{cases}$$

where D_i represents the new commuting distance of the *i*th commuting record; $D_i^{'}$ 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.

S_j^{*} was calculated based on the following formula:

$$S^{*} = \frac{D_j^{*}}{T_j^{*}}$$

where D_j^{*} is the mean commuting distance of mode *j* for $D_i^{'}$ greater 0; T_j^{*} is the mean commuting time of mode *j* for $D_i^{'}$ greater 0.

When measuring job accessibility, we defined 60 min as the threshold time for public transportation and 30 min 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 and 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.

3.3. Descriptive statistics

The distribution of individual and spatial factors, commuting distance, and commuting time has a distinct pattern per *hukou* type (Table 1).

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 2).

Table 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.

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 min).

As shown in Table 3, this result may be explained by the fact that locals are more likely than migrants to commute by 'faster' modes of transport like motorcycles (15.2% vs 5.9%) or private cars (35.2% vs 12.2%).

4. Spatial analysis

4.1. Distribution of local and migrant workers

The spatial distribution of workers by occupation is displayed in Fig. 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.

Table 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

Table 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%

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.

4.2. Commuting pattern

The overall commuting pattern of workers by occupation is shown in Fig. 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.

5. Results

Table 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).

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

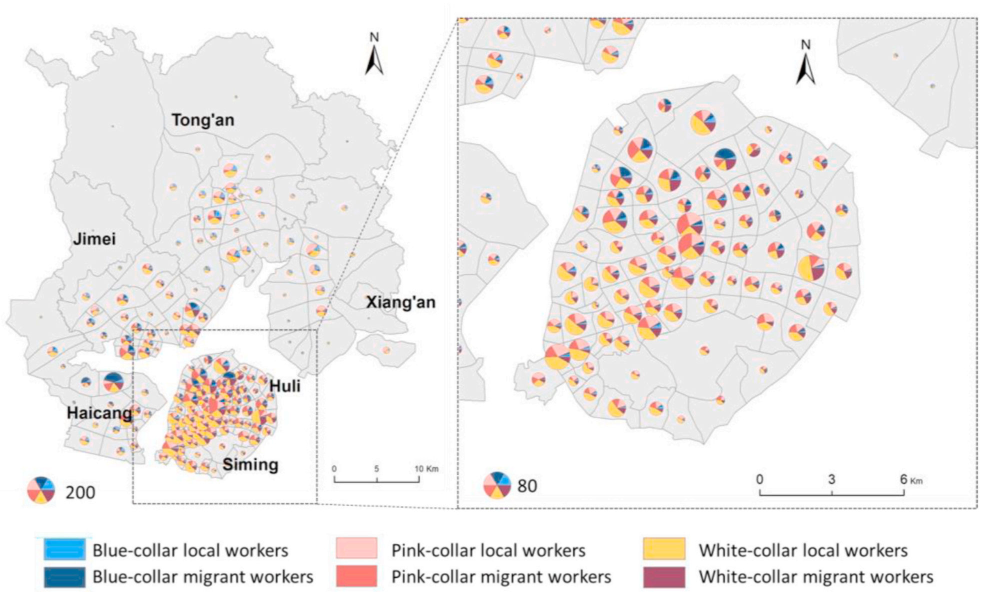

Fig. 3. Distribution of workers by occupation. Note: We only consider three types of occupations, so some areas have no population. For example, there are a certain number of farmers in the periphery of the city, but the map shows no population.

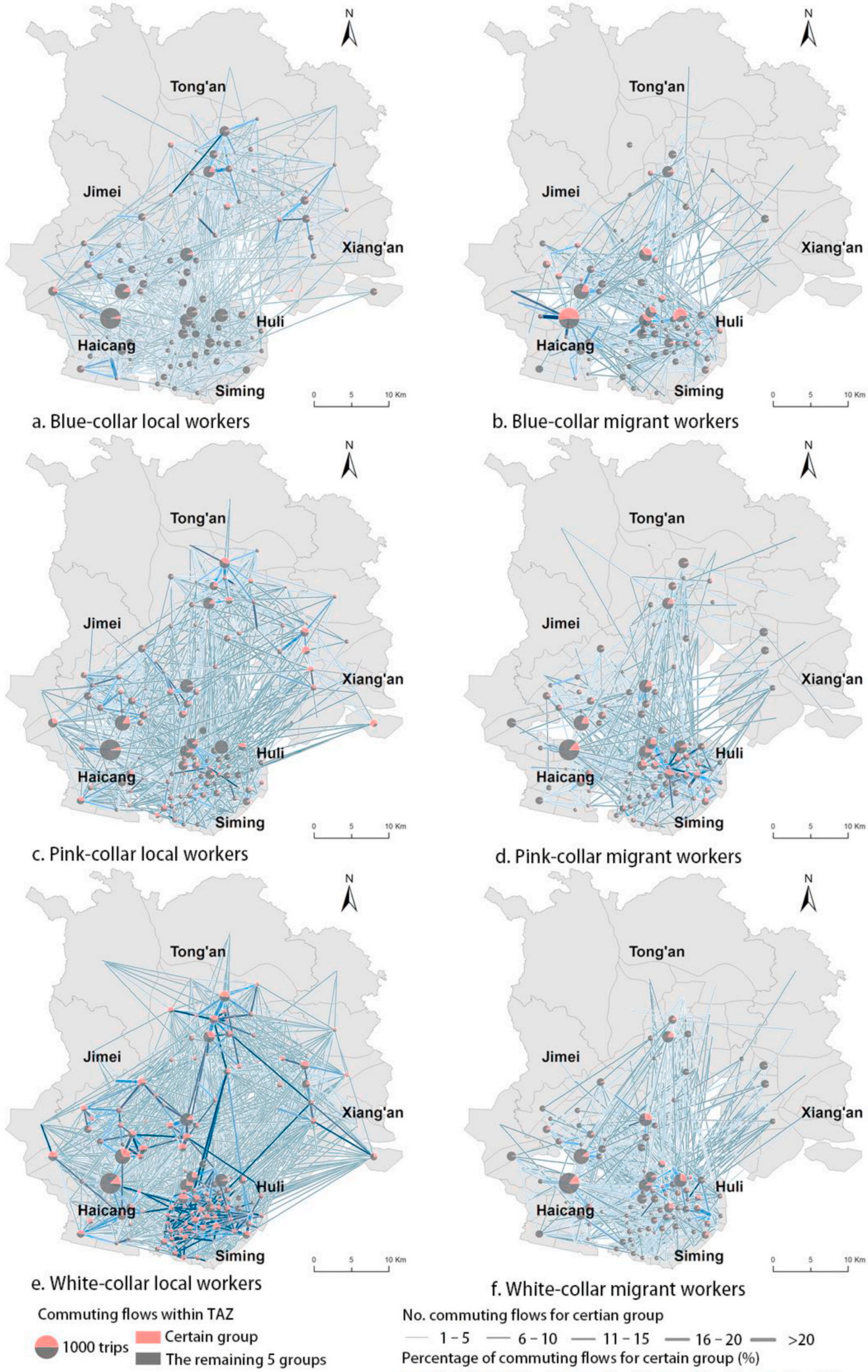

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Fig. 4. Commuting flows of workers by occupation. Notes: the size of the circle in the pie charts represents the total commuter flow of the six groups; The certain group is consistent with the layer name.

Table 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[a]	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.

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 and 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 (van Ham et al., 2001; McQuaid and 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. Fig. 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 and 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.

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 and 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. A recent study of Zhao and Cao (2020) also show that the areas with larger migrant populations in Shanghai city have less long commuters. Based on these findings, 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 1) 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 and 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. New policies should be made to reduce the commuting time of disadvantaged groups, because long commuting time has a negative impact on employment and 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 socio-economic 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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Appendix 1. 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%

[a] It is normal that the analysis of individual data from travel survey covering a quite large spatial area would produce low R^2 value (Boarnet and Hsu, 2015; Schwanen et al., 2003), because individuals are often heterogeneous in terms of their attitudes, actions, and behaviors travel (Mercado and Páez, 2009; Turner and Niemeier, 1997).

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