# A multi-scale study of the scale effect on the spatial mismatch in urban centres: A case study of Tianjin

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**Abstract.** Currently, the urban job-housing problem is increasingly severe, and scale effects strongly influence the results of studies. To achieve a more comprehensive and accurate analysis and assessment of the job-housing relationship in urban centers, this study takes Tianjin as an example, and with the help of Baidu Map Insight spatial and temporal big data, adopts spatial analysis, regression analysis and other methods to establish a multi-scale job-housing relationship impact model with administrative districts, streets and TAZs (traffic analysis zones) as the research units, which provides a methodological reference for weakening the scaling effect. The study found that (1) in terms of research methodology, multi-scale composite studies can effectively weaken the impact of scale variation on research results; (2) in the correspondence between the influencing factors and the study level, with the gradual refinement of the study level, the type of influencing factors was transformed from the urban construction category to the personal attribute category, and the different influences have different primary actiont levels; (3) in terms of the mechanism of influence, some of the personal attribute factors have a strong regularity in the mechanism of influence, while those of the urban built factors are more complex, which suggests that the urban built factors have a high sensitivity to the scale effect.

**Keywords:** spatial mismatch; job-housing; scale effect; urban centre.

## 1 Introduction

As urbanization advances, the spatial separation problem in large and medium-sized cities has grown increasingly serious, with the average commuting distance and commuting time of urban residents growing, and the proportion of happy commuters within 5 kilometers of China's major cities declining year-on-year for three consecutive years[1].In the study of job-housing issues, the research scale is the focus, mainly because of the following two points: (1) different scales can reflect different contents, and the complexity of the urban job-housing relationship makes it difficult to be explained clearly from a single scale; (2) changes in the research scale have a significant


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impact on the results of the study, which is known as scale effect, and it was firstly put forward by Western scholars, Small[2].

In the measurement of job-housing relationship, when the job-housing ratio is 1, it means that the region has reached the state of job-housing balance. This leads to the fact that the larger the spatial analysis unit, the easier it is to achieve equilibrium[3]. Conversely, the smaller the study unit, the greater the more dramatic the change in the job-housing ratio[4,5]. The conclusions of a study based on a larger scale may differ considerably when implemented into one of the smaller scale research units; at the same time, the conclusions of a study based on a smaller scale are difficult to form the conclusions of a larger scale study by simple combination. Therefore, the findings of a single-scale study cannot fully represent the true job-housing situation.

Existing studies often measure job-housing relationships from scale analysis units such as administrative districts, streets, TAZs (traffic analysis zones), and buffer zones of different radiuses[6-9], which can be summarized into three types of scales: macro, meso, and micro. It was found that more in-depth and comprehensive analyses can be obtained when multiple levels of research are complementary to each other[10,11]. Macro and meso scales can effectively grasp the overall situation, but are not detailed enough; micro scales can make up for this shortcoming, but they do not well reflect regional phenomena, which can be supplemented by studies at meso and macro scales. Most of the current research on job-housing relationships specializes in a single scale and lacks multi-scale research.

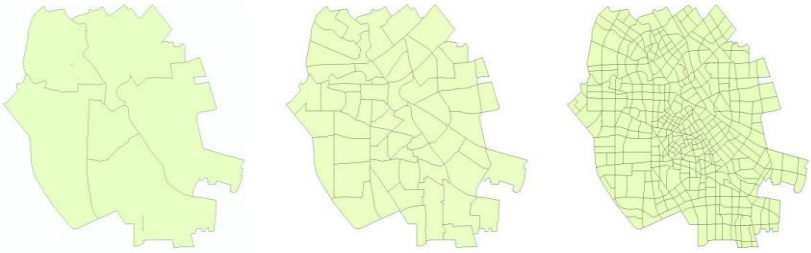
In summary, this study will focus on the following questions: (1) Can the multilevel composite analysis comprehensively and in-depth conclusions of the study of job-housing relationships? (2) What are the characteristics in terms of the correspondence between the influencing factors and the study levels, and the influencing mechanisms?

## 2 Method

### 2.1 Subjects and study levels

This study takes the central city of Tianjin as the research object. The central city is the political, economic, and cultural center of Tianjin. For Tianjin, the spatial mismatch in the central city stems from the historical legacy on the one hand. On the other hand, it is due to the early start of its urban development and rapid urbanization that fails to take care of the balanced development needs of the city's occupational and residential relations. Many city centers in China and worldwide face similar situations, making Tianjin typical for the study.

In order to alleviate the constraints of scale effects in the study of job-housing relations, this study compounds three levels of study with the help of existing administrative divisions, including administrative districts, streets, and TAZ, as shown in Figure 1. The study area contains six administrative districts, 65 streets, and 435 TAZ. Similar traffic characteristics and strong traffic associations within the same TAZ can be used to simplify complex networks.



a. Administrative districts b. Streets C. TAZs

**Fig. 1.** Graphical representation of each study level

## 2.2 Research Methods

The study adopts a one-way regression method, with commuting distance as the dependent variable, and the research data mainly comes from Baidu Map Insight. One of the essential steps is the selection and hierarchical matching of influencing factors.

Preliminary screening was carried out by analyzing the reasons for the formation of the status quo of spatial separation, summarizing the relevant domestic and foreign literature, and then combining the frequency of various types of factors in the established high-level literature, the objective conditions of whether the factors can be quantified, and the actual situation of whether the data are publicly available. There are seven urban built environment factors, including city scales, compactness, Urban public transportation, land use mix, and urban functional arrangement[12-15]. Nine personal attributes and socio-economic factors, including gender, age, special life stages, educational background, income, availability of a private vehicle, commuting mode, and house price[16-21].

Further, based on the established research and logical deduction for research level matching and influencing factors detailing, a research schedule of influencing factors of job-housing relationship under the multi-scale perspective was derived, as shown in Table 1 below.

**Table 1.** Research program on factors influencing the job-housing balance under a multi-scale perspective

| Influencing Factors | Specific indicators and their acronyms | I | II | III |
|---|---|---|---|---|
| Scales | Area (A) | • | • | • |
| | Number of resident population (NR), workforce(NW) | • | • | • |
| Compactness | Density of resident population(DR), workforce(DW) | • | • | • |
| | Road network density (RND) | • | | |
| Urban public | Number of rail stations($N_{RS}$), rail interchanges($N_{RI}$) | • | • | |
| transportation | Density of rail stations($D_{RS}$), rail interchanges(D-) | • | • | |

| | | | | |
|---|---|---|---|---|
| | Number and density of public transport stations($N_{PS}$, $D_{PS}$) | • | • | • |
| Mixed land use | Urban function mixing degree (UFMD) | • | • | • |
| Urban functional arrangement | Number of POIs in each category: residential ($N_{RPOI}$), medical ($N_{MPOI}$), education and training ($N_{ETPOI}$), exercise and fitness ($N_{EFPOI}$), cultural and media ($N_{CMPOI}$), government agency ($N_{GPOI}$), corporate enterprise ($N_{CEPOI}$), financial ($N_{FPOI}$), shopping ($N_{SPOI}$), accommodation service ($N_{ASPOI}$), beauty ($N_{BPOI}$), catering ($N_{CPOI}$), tourist attractions ($N_{TAPOI}$), leisure and entertainment ($N_{LEPOI}$) | • | • | • |
| | Density of POIs in each category: residentia(DRPOI), medical($D_{MPOI}$), education and training($D_{ETPOI}$), exercise and fitness($D_{EFPOI}$), cultural and media($D_{CMPOI}$), government agency($D_{GPOI}$), corporate enterprise($D_{CEPOI}$), financial(DFPOI), shopping($D_{SPOI}$), accommodation service($D_{ASPOI}$), beauty($D_{BPOI}$), catering($D_{CPOI}$), tourist attractions($D_{TAPOI}$), leisure and entertainment($D_{LEPOI}$) | • | • | • |
| gender | Percentage of resident population/ workforce whose sex is male($PSR_M$, $PSW_M$), famale($PSR_F$, $PSW_F$) | | • | • |
| age | Percentage of resident population/ workforce aged 18 and under($PAR_{18-}$), 18-24($PAR_{18-24}$, $PAW_{18-24}$), 25-34($PAR_{25-34}$, $PAW_{25-34}$), 35-44($PAR_{35-44}$, $PAW_{35-44}$), 45-54($PAR_{45-54}$, $PAW_{45-54}$), 55-64($PAR_{55-64}$, $PAW_{55-64}$), 65 and above($PAR_{65+}$, $PAW_{65+}$) | | • | • |
| Special life stages | Percentage of resident population at junior high school($PR_{JH}$), high school($PR_H$), Percentage of resident population/ workforce attending university($PR_{BD}$, $PW_{BD}$), in postgraduate studies($PR_{MD}$, $PW_{MD}$), pregnant($PR_P$, $PW_P$), with a 0-1-year-old child at home($PR_{0\text{-}1CH}$, $PW_{0\text{-}1CH}$), with a 1-3-year-old child at home($PR_{1\text{-}3CH}$, $PW_{1\text{-}3CH}$), with a 3-6-year-old child at home($PR_{3\text{-}6CH}$, $PW_{3\text{-}6CH}$), with primary school children at home($PR_{PCH}$,$PW_{PCH}$), with junior high school student at home($PR_{JHH}$, $PW_{JHH}$), with high school student at home($PR_{HH}$, $PW_{HH}$), with pregnant women at home($PR_{PH}$,$PW_{PH}$) | | • | • |
| Educational background | Percentage of resident population/ workforce with educational background of upper secondary and below($PEBR_{H-}$, $PEBW_{H-}$), Percentage of resident population with Associate degree($PEBR_A$, $PEBW_A$), Percentage of resident population with educational attainment of bachelor's degree and above($PEBR_{B+}$, $PEBW_{B+}$) | | • | • |
| Income | Disposable income per capita(DI) | • | | |
| | Percentage of resident population/ workforce with monthly income of 2,499CNY or less ($PIR_{2499-}$, $PIW_{2499-}$), 2500-3999CNY ($PIR_{2500\text{-}3999}$,$PIW_{2500\text{-}3999}$), 4000-7999CNY ($PIR_{4000\text{-}7999}$, $PIW_{4000\text{-}7999}$), 8000-19999CNY ($PIR_{8000\text{-}19999}$, $PIW_{8000\text{-}19999}$), 20000CNY and above ($PIR_{20000+}$, $PIW_{20000+}$) | | • | • |
| Availability of a private vehicle | Percentage of resident population/wworkforce with a private car($PWCR_Y$, $PWCW_Y$), without a private car($PWCR_N$, $PWCW_N$) | | • | • |
| Commuting mode | Percentage of resident population/ workforce commuting by metro($PCR_M$, $PCW_M$), by public transport($PCR_P$, $PCW_P$), by bicycle($PCR_B$, $PCW_B$), on foot($PCR_W$, $PCW_W$), using car as a mode of commuting($PCR_C$, $PCW_C$) | • | • | • |
| House price | House price(HP) | • | • | |

*I is for large scale; II is for medium scale; III is for small scale.

# 3 Result

The quantified impact factors were fitted to the data with the one-way average commuting distances of residents ($AOCD_R$) and the workforce ($AOCD_W$) to obtain an impact model. The independent variables with significant effects are recorded in Table 2.

**Table 2.** Summary of regression results

| Inde-pendent variable | The dependent variable is $AOCD_R$ | | | The dependent variable is $AOCD_W$ | | | Independent variable | The dependent variable is $AOCD_R$ | | | The dependent variable is $AOCD_W$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Indicators | A | S | TAZ | A | S | TAZ | Indicators | A | S | TAZ | A | S | TAZ |
| $NR$ | | | ↑ | | | ↓ | | | | | | | |
| $DR$ | ↓ | | | | | ↓ | $DW$ | | | | | ↑ | ↑ |
| $N_{RS}$ | | | | ↑ | | | $D_{PS}$ | | | | ↓ | | |
| $N_{RPOI}$ | | | | | | ↓ | $D_{RPOI}$ | | | | | | ↓ |
| $N_{MPOI}$ | | ↓ | | | | | $D_{CEPOI}$ | ↓ | ↓ | | | | |
| $N_{ETPOI}$ | | | | | ↑ | | $D_{SPOI}$ | | ↓ | | | | |
| $N_{SPOI}$ | | ↑ | | | | | $D_{CPOI}$ | ↓ | ↓ | | | | |
| $N_{CPOI}$ | ↓ | ↓ | | | | | $D_{ASPOI}$ | ↓ | | | | | |
| $N_{BPOI}$ | | | | | | ↓ | $D_{LEPOI}$ | ↓ | | | | | |
| $N_{ASPOI}$ | ↓ | | | | ↑ | | $D_{GPOI}$ | | ↓ | | | | |
| $N_{LEPOI}$ | | ↓ | | | | ↓ | $D_{MPOI}$ | | ↓ | | △ | | |
| $N_{MPOI}$ | | ↓ | | | | ↓ | $D_{CMPOI}$ | | ↓ | | | | |
| $N_{CMPOI}$ | | ↓ | | ↑ | ↑ | | $D_{LPOI}$ | | ↓ | | ↓ | | |
| $N_{LPOI}$ | ↓ | ↓ | | | | | $D_{ETPOI}$ | | | | | | |
| $N_{ETPOI}$ | ↓ | ↓ | | | | | $D_{EFPOI}$ | ↓ | | | | | |
| $HP$ | | ↓ | | ↑ | ↑ | | $DI$ | | | | ↑ | | |
| $PIR_{2499-}$ | | | | | ↓ | ↓ | $PIW_{2499-}$ | | | | | ↓ | ↓ |
| $PIR_{2500-3999}$ | | | | | | ↑ | $PIW_{2500-3999}$ | | ↑ | | | ↓ | ↑ |
| $PIR_{8000-19999}$ | | | | | ↑ | ↑ | $PIW_{4000-7999}$ | | ↑ | | | ↓ | ↓ |
| $PIR_{20000+}$ | | | | | ↑ | ↑ | $PIW_{8000-19999}$ | | ↓ | | | ↑ | ↑ |
| $RND$ | ↑ | | | | | | $PIW_{20000+}$ | | ↓ | | | ↑ | ↑ |
| $PSR_M$ | | | | △ | | ↑ | $PSW_M$ | | ↓ | | | | ↑ |
| $PSR_F$ | | | | △ | | ↓ | $PSW_F$ | | ↑ | | | | ↓ |
| $PCR_C$ | ↑ | | | | ↑ | ↑ | $PCW_C$ | | ↑ | | | | |
| $PCR_M$ | ↓ | ↑ | ↑ | | | | $PCW_M$ | | ↓ | | ↓ | ↑ | ↑ |
| $PCR_P$ | | ↑ | | | ↓ | ↓ | $PCW_P$ | ↑ | | | | ↓ | ↓ |
| $PCR_B$ | | ↓ | ↓ | | | | $PCW_B$ | | | | ↓ | ↓ | ↓ |
| $PCR_W$ | | ↓ | ↓ | | | | $PCW_W$ | | ↑ | | ↑ | ↓ | ↓ |
| $PAR_{18-24}$ | | | | | | ↑ | $PEBR_{H-}$ | | | | | | ↑ |
| $PAR_{25-34}$ | | ↑ | | | | ↑ | $PEBR_A$ | | | | | ↓ | ↓ |
| $PAR_{35-44}$ | | | | | | ↓ | $PEBR_{B+}$ | | | | | ↑ | ↑ |
| $PAR_{55-64}$ | | | | | ↓ | ↓ | $PEBW_{H-}$ | | ↑ | | | ↓ | |
| $PAR_{65+}$ | | ↓ | ↓ | | | ↓ | $PEBW_A$ | | | | | ↓ | |
| $PAW_{18-24}$ | | | | | ↑ | ↑ | $PEBW_{B+}$ | | ↓ | | | ↑ | |
| $PAW_{25-34}$ | | | | | ↑ | ↑ | $PAW_{55-64}$ | | | | | | ↓ |
| $PAW_{45-54}$ | | | | | | ↓ | $PAW_{65+}$ | | | | | ↓ | ↓ |
| $PWCR_Y$ | | ↑ | ↑ | | ↑ | | $PWCW_Y$ | | | | | ↑ | ↑ |
| $PWCR_N$ | | ↓ | | | ↓ | | $PWCW_N$ | | | | | ↓ | ↓ |
| $PR_{JH}$ | | ↓ | | | | | $PW_{BD}$ | | | | | | ↑ |
| $PR_H$ | | | | | ↑ | | $PW_{MD}$ | | ↓ | | | | ↑ |
| $PR_{BD}$ | | | | | | ↑ | $PW_P$ | | ↓ | | | ↑ | |
| $PR_{MD}$ | | ↓ | | | | ↑ | $PW_{PH}$ | | | | | ↑ | |
| $PR_P$ | | | | | | ↓ | $PW_{0-1CH}$ | | | | | ↑ | |

| Inde-pendent variable | The dependent variable is $AOCD_R$ | The dependent variable is $AOCD_W$ | | Independent variable | The dependent variable is $AOCD_R$ | The dependent variable is $AOCD_W$ | |
|---|---|---|---|---|---|---|---|
| $PR_{PH}$ | ↓ | | | $PW_{1\text{-}3CH}$ | | ↑ | ↑ |
| $PR_{0\text{-}1CH}$ | | ↓ | ↓ | $PW_{3\text{-}6CH}$ | | ↑ | ↑ |
| $PR_{1\text{-}3CH}$ | | | ↓ | $PW_{PCH}$ | | ↓ | ↓ |
| $PR_{3\text{-}6CH}$ | | | ↓ | $PW_{JHH}$ | | ↓ | ↓ |
| $PR_{PCH}$ | | ↓ | ↓ | $PW_{HH}$ | | | ↓ |
| $PR_{JHH}$ | ↓ | | | | | | |

* "↑" indicates linear positive correlation and a segment in the binomial where the fitted data are already presenting mainly positive correlation; "↓" denotes linear negative correlation and a segment of the binomial where the fitted data are already presenting predominantly negative correlation; "△" indicates a binomial relationship and a more symmetrical parabola, and blank indicates no significant association; A is for administrative district; S is for streets.

# 4 Conclusions

The regression results and mechanisms of influence are analyzed and summarised separately according to the influencing factor categories and study levels.

(1) Scales: Population size is significant at the TAZ level only, with NR being proportional to the $AOCD_R$ and inversely proportional to $AOCD_W$.

(2) Compactness: Population aggregation has a significant effect at all three study levels. It can be summarised as follows: within a certain level of agglomeration, the higher the DR and DW, the higher the likelihood of employment nearby; when the DR is too high, the supply of jobs exceeds the demand, and when the NR is too high, there is not enough living space and house prices rise, both of which lead to a situation of spatial separation and an increase in the commuting distance. RND is positively correlated with commuting distance in conjunction with road width and on-street parking conditions.

(3) Urban public transportation： Public transport stops have a significant impact at the ward level only, clarifying their primary level of effect. In particular, $N_{RS}$ is mainly positively correlated with $AOCD_W$, and $D_{PS}$ is negatively correlated with it, which suggests that the metro is significantly different from buses. It can be analyzed with the effects of commuting modes.

(4) Mixed land use and urban functional arrangement: The UFMD did not have a significant effect on commuting distance, but the number and density of urban functional POIs essentially affected it, mainly on the street study level and the $AOCD_W$. In other words, the clustering of urban functions at the street level can effectively shorten the commuting distance and inhibit the further development of spatial mismatch.

(5) Gender: The gender factor has a strong influence at both the street and TAZ study levels, with the proportion of males being positively correlated with the $AOCD_W$ and the proportion of females being negatively correlated. To reduce the overall commuting distance, more jobs targeting female recruitment can be created in and around residential areas. However, from another perspective, this practice will aggravate the shackles of the traditional thinking that "women should give preference to taking care of their families over their careers," creating obstacles to women's independence and autonomy and thus intensifying the gender dichotomy. This also shows that compre-

hensive consideration should be considered in formulating the relevant policies to uphold fairness and justice.

(6) Age: The focus of life differs for each age group, but the pursuits are similar for the same age group. Therefore, the effect of age has a strong regularity at the street and TAZ study levels. With a dividing line of 35 years of age, the proportion of the population aged 18-34 is directly proportional to the commuting distance, and the proportion of the population aged 35 and over is inversely proportional.

(7) Special Life Stages: At the street level, $PR_{MD}$, $PW_{MD}$, $PR_{P}$, and $PW_{P}$ are negatively correlated with the dependent variable due to maternity and school residency. At the street and TAZ level, the proportion of the population with a preschooler at home is positively correlated with commuting distance. In contrast, the proportion of the population with a student at home is mainly negatively correlated with commuting distance due to local schooling policies nearby. However, the impact of policies is difficult to quantify, and most of the relevant data are confidential, so there are few quantitative studies on it.

(8) Educational background: The effect of educational qualifications on spatial mismatch is more pronounced at the street level. The essential regularity can be summarised as the proportion of the population with tertiary education and below is inversely proportional to the commuting distance. In contrast, the proportion of the population with a bachelor's degree and above is positively proportional.

(9) Income: The effect of income on commuting distance is strong, and the mechanism is regular at the two extreme intervals of the highest and lowest incomes. Due to the existence of urban villages, groups with incomes of 2,499CNY and below can combine low rents and low transport costs in the study area, achieving a state of relative job-housing balance, which is inversely proportional to the dependent variable. Income groups above 8,000 seeking a higher quality of life positively correlate with commuting distance.

(10) Commuting modes: The proportion of people commuting by metro and by car is mainly positively correlated with commuting distance; the proportion of people using walking, cycling, and public transport as commuting modes is mainly negatively correlated with it. This suggests that promoting non-motorized transportation not only contributes to low-carbon goals but also encourages spatial job-housing balance.

(11) Availability of a private vehicle: The proportion of people with a car is positively correlated with commuting distance, and the proportion of people without a car is negatively correlated with it, with a clear pattern of influence.

(12) House prices: House prices are directly proportional to $AOCD_{W}$ and inversely proportional to $AOCD_{R}$. The higher the house prices within an area, the more difficult it is for the workforce to achieve residence nearby.

Based on the specific analysis of the types of influencing factors, it is further condensed to answer the research question through the influencing factors and influencing mechanisms at each level, and the relationship of changes between different levels: (1) In terms of research methodology, composite multi-scale research can weaken the impact of scale effects, and this methodology can be widely applied in research on occupational and residential issues aimed at reducing the impact of scale effects. (2) In terms of the types of influencing factors and their correspondence with the study levels,

from the administrative district level to the TAZ level, the significant influencing factors underwent a shift from urban built-up factors to personal attributes and socio-economic factors as the study units were reduced in size. Different influencing factors have different levels of significant effects. A typical example is that various urban functions play a more decisive role at the street level. Commuting distance is more sensitive to fluctuations in the age factor at the TAZ level. Thus, compounding multiple levels of research can help to obtain more comprehensive and objective conclusions. (3)In terms of the influence mechanism, the degree of significance and the influence mechanism of the same factor is not the same at different levels of the study. However, personal attributes and socio-economic factors are basically able to reflect a strong regularity at all scales, including age, gender, education, income, commuting mode, and availability of a private vehicle, which suggests that the scale effect is relatively weaker on the personal attributes and socio-economic factors, but significant on the urban built factors.

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