# Does public transit improvement affect commuting behavior in Beijing, China?: A spatial multilevel approach

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**Abstract:** Developing countries like China have experienced substantial city transformations over the past decade. City transformations are characterized by transportation innovations that allow individuals to access to speedy commuting modes for work activities and offer potential influences on commuting behavior. This paper examines the potential effects of subway system expansion in Beijing on commuting behavior. Our methodological design controls for spatial effects by employing Bayesian multilevel binary logistic models with spatial random effects. Using cross-sectional individual surveys in Beijing, the results suggest that there is a significant rise in subway commuting trips while non-motorized and bus commuting trips are reduced with the new subway expansion. Model comparison results show evidence about the presence of spatial effects in influencing the role of built environment characteristics to play in the commuting behavior analysis.

**Keywords:** travel mode choice, subway expansion, multilevel model, China

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# 1 Introduction

Modern-day rail transit network expansions have provided a textbook case and opportunity of paramount scientific value in generating evidence for the conceptual foundations that underlie much of variations in a commuting mode choice. A growing body of literature investigates the connection between commuting behavior and rail system investments in particularly based on the US evidence. Coupled with rapid public transit improvements in the past decade, interests in this research field have been increasingly shifted into evidence from developing countries. A number of studies found that public transit improvements could lay the foundation for environmentally-friendly urban transformations by reducing motorized travel and stimulating complementary non-motorized transportation modes such as walking and bicycling (Litman, 2015; Cervero, 1994; Besser and Dannenberg, 2005). But to what extent are public transit improvements associated with the increased transit ridership and reduced commuting trips by vehicle, particularly in large, rapidly developing countries?

China has experienced phenomenal transportation system transformation in the past two decades. This transformation has come alongside massive transportation investments within and between cities that could bring heterogeneous amenity capitalization effects on land markets (Zheng and Kahn, 2008; Wu and Dong, 2014; Wu et al., 2015a; Wu et al., 2015b). This rapid but differential spatial expansion in the subway infrastructure also has potential impacts on commuting behavior. A key policy target is to mitigate commuting costs and improve low-carbon environment and pollution conditions for cities and the wellbeing of its citizens. In addition, Chinese cities have a comprehensive public transit infrastructure and much more diverse commute modes compared to US cities. (Peng, 1997; Cervero and Day, 2008; Pan et al., 2009; Pan et al., 2013; Zhao, 2013). However, not much is known about the influences of public transit improvements and spatial factors on commuting behavior in Chinese cities.

This paper examines whether and to what extent changes in subway accessibility can reinforce the subway use for commuting. Our investigation focuses on the rail transit development for strengthening the connection between central city and suburban areas in Beijing. To carry out the investigation, we employed two rounds of cross-sectional individual surveys to identify individuals' commonly-used commuting modes and demographic characteristics. Methodologically, existing literature on the evaluation of public transit improvements has so far paid little attention to the role of spatial effects in the commuting behavior analysis. People residing in the same area may travel in a similar way due to unobserved or hard-to-measure factors such as the quality of public transit system and amenities. In addition, spatial dependency may also exit between adjacent neighborhoods. If these spatial relationships are not handled appropriately, they may lead to incorrect conclusions (Hong & Shen, 2013). To explicitly address this concern, we used the Bayesian multilevel logistic regressions with spatial random effects in the commuting behavior analysis to assess the sensitivity of the results.

# 2 Literature review

Research on commuting behavior implications of rail transit development can be traced back at least to Mitchell and Rapkin (1954). This study fits into several strands of literature. First, there is a substantial empirical literature dealing with the driving forces of commuting mode choice (Cervero and Radisch, 1996; Boarnet and Crane, 2001). Much of it is concerned with variations in job-housing mismatching, mixed land uses and self-selection sorting, which are important but not are the focus of this study (Cervero, 1989; Shen, 2000; Cervero, 2002; Handy et al., 2005; Cao et al., 2006; Mokhtarian and Cao, 2008; Cao et al., 2009; Wang and Chai, 2009; Wang et al., 2011; Cao and Schoner, 2014). The main policy implication from these studies is to find ways for reducing auto dependency and promoting the use of non-motorized transportation modes. Typically, empirical studies have focused on comparing travel patterns such as transit commuting share, numbers of trips or travel distances across different commuting modes at rail-accessed areas with at comparable locations (areas with similar built environment characteristics) where rail transits do not exist. Although methodological-related designs vary across studies, most existing studies found the strong effects of transit-based housing and transit-oriented development (TOD) on public transit use, at least in the short-run (Cervero, 1994; Lund et al., 2006).

Second, China's recent experience of rapid transportation infrastructure constructions and urban growth provides a textbook scenario for studying the potential effects of public transportation improvements on commuting mode choices. Existing studies have well documented socio-spatial implications of transportation infrastructure expansions on real estate prices and local economic growth in China (Zheng and Kahn, 2013; Wu et al., 2015). However, little is known about commuting behavior implications. Cervero and Day (2008) looked at the impact of home relocations on commuting mode choice of local residents among three selected neighborhoods in Shanghai. By controlling for the employment accessibility, their results showed that home relocations increase movers' car travel and commuting duration. They also found that relocating to an area near a metro station encourages commuting mode shifts from non-motorized commuting to public transit commuting. Wang et al. (2011) used a activity–travel behavior survey in Beijing and found that residents living in the urban fringe areas have high shares of motorized commuting travel than people living in the central city areas. Zhao (2010) found that the dispersed land development in Beijing's urban fringe areas leads to the increased commuting distance and car use for local residents. Yang et al. (2012) examined the transformation of job concentrations in Beijing, and suggested that Beijing should rebalance its city structures by stimulating the growth of suburban areas through public transit development. By using the traditional logistic regressions, Pan et al. (2013) found that working adults tend to commute by subway after they moved to the suburban areas, and car ownership has been increasing significantly despite of the recent subway system expansion in Shanghai. These studies have shed light on the role of public transit improvements on commuting mode choices in Chinese cities. However, little is known about the importance of incorporating the spatial issues (e.g., spatial dependency among people in the same geographic area) in evaluating the effects of public transit improvements on commuting behavior in China.

Finally, this study is related to the land use-travel literature that applies a multilevel approach to consider the potential correlation among travelers in the same household or living in the same area (Bhat, 2000; Schwanen et al., 2003; Hong & Goodchild, 2014). For example, Hong et al., (2014) analyzed the relationship between built environment factors measured at different scales and motorized travel by adopting a multilevel framework with spatial random effects. They found that people living in the same traffic analysis zone (TAZ) have a relatively small correlation in commuting behaviour but there is a clear spatial pattern between TAZs. Bottai et al. (2006) incorporated the group-variances of families and individuals, and found that people from the same household are likely to have similar travel behavior patterns than individuals from different families. In general, most empirical studies supported the importance of using spatial models to analyze the relationship between urban form and travel behavior. However, multilevel models cannot account for the potential correlation between close neighborhoods. That is to say, results from multilevel models can be afflicted by fundamental spatial autocorrelation problems that are important in the geographic data context (horizontal spatial dependence). As shown in Hong and Shen (2013)'s paper, incorporating the horizontal spatial dependence into the estimation of multilevel models offers more hope of finding solutions to this identification problem.

In sum, we contribute to the existing literature in three ways. First, we are among the first to investigate the effects of public transit improvements on commuting mode choice in a fast urbanizing country where rail transit systems have been rapidly increasing, neighborhoods are much denser than the US and European countries. Second, we explore the dynamic influence of the change in rail transit accessibility on commuting mode choice at the local area level. The extant literature focuses on the household surveys conducted at a single time period, and much remains to be done regarding the dynamic effects of public transit improvements. This study uses cross-sectional surveys before and after the opening of new subway lines to assess its potential impacts. It would be worth noting that the 2005 and 2009 surveys applied in this study are not individual-level panel data, but share very similar questionnaire structures. We acknowledge this data limitation. Future works are encouraged to use a panel data structure to examine the impact of new rail transit investments based on the same group of households. Third, we apply what we believe a more reliable econometric approach (a Bayesian multilevel logit model with spatial random effects) in the empirical analyses so as to simultaneously consider the vertical spatial dependence and horizontal spatial dependence. As far as we know, this is an innovative application in China.

# 3 Methodology

## 3.1 Data and variables

Figure 1 shows the distribution of transportation systems (including subway lines, road networks and bus stations) in Beijing. While bus and road networks have remained stable in Beijing, there were dramatic improvements in subway networks around 2008. 4 new subway lines (Line 4, 5 8A and 10A) opened during October 2007 and February 2009. Ideally one can treat the opening time of each station or line separately. To simplify the analyses, we treat them as a single event given that they opened all around 2008. In terms of spatial structures, this has expanded the subway network to link edge towns with central city areas, and link the Olympic park with the main subway network. The researchers from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences conducted two large scale individual surveys in 2005 and 2009 to examine the living environment in the Beijing metropolitan area. Even though these are not travel surveys, the survey content includes socio-demographics and commuting information. This enables us to utilize these two surveys to examine the influences of new subway system expansion on commuting mode choice.

[Figure 1 is here]

Questionnaires were distributed randomly at the neighborhood level (jie dao) and in proportion to the total population calculated based on the 2000 population census (Zhang et al., 2006). The respondents were asked to state if they have a full time job, and if they do not have a full time job, they will not be suitable to answer the commuting questions in the questionnaire. The surveys asked "what is your main commuting mode to work". It indicates that this study only considers commuting behavior. Further studies are encouraged to examine the differential effects of new rail transit investments on commuting and non-work related travel behavior. Meantime, we cannot observe if a respondent uses a combination of multiple commuting modes together when commuting. We acknowledge this limitation. After cleaning and processing the data, 9462 valid respondents are included in the analyses. Our dependent variables include the uses of subway, automobile (including private cars and taxi), bus (including company shuttle bus and public bus), bicycle and walk[1] for commuting purposes. For the empirical analyses, we also include diverse socio-demographics and two built environment factors. *Population density* is calculated based on the 2000 City Population Census reported by the National Bureau of Statistics of China (NBSC). The job density information is obtained from the 2nd City Employment Census conducted in 2001 by NBSC (see also Harris et al., 2013). The *Employment accessibility* indicator is measured by the weighted job density (*W_JDEN*) based on the following equation:

$$W\_JDEN_i = \sum_j JDEN_j \times e^{-(\frac{dis_{ij}}{d})^2} \tag{1}$$

where $JDEN_j$ , $dis_{ij}$ $and$ $d$ represent the job density of neighborhood (*jiedao* in Chinese, the basic census unit in Beijing) *j*, the distance between neighborhood *i* and *j*, and the distance decay parameter over geographical areas, respectively. While the value of distance decay parameter may remain as a limitation that needs future research, we set $d$ = 2 by following the recent empirical research conducted in Beijing (Ding et al, 2010). These two built environment factors, even though they were calculated differently, are often utilized in the land use-travel studies (Ewing and Cervero, 2010).

[Table 1 here]

Descriptive statistics are shown in Table 1. It shows that the 2009 survey includes slightly more young people, large households and relative wealthy households. The number of subway stations increases significantly in the 2009 survey compared to 2005 survey on average, largely because of the new subway expansion. The result also shows significant differences in the commuting mode share. Higher percentages of people use subway or private cars in 2009 than 2005. This could be due to both the subway system expansion and economic growth. In addition, a lower percentage of people use non-motorized modes and bus in 2009 compared to 2005. Overall, around 87 percentages of respondents tend to use low-carbon transportation modes such as subway, bus and walk to commute in 2005, although the total share of these transportation modes dropped in the 2009 survey.

### 3.2 Research design and econometric models

Our aim is two-fold. First, we examine how the new subway expansion in the Beijing metropolitan area affects individuals' commuting mode choice. Second, we incorporate spatial effects in the analysis to assess the sensitivity of the results. We begin by examining

[1] To simplify the analyses, we combined bus, walk and bicycle as one commuting mode group since they shared low-cost and low-carbon sustainable transportation characteristics.

the difference in communing behavior between two years (i.e., 2005: before the subway expansion and 2009: after the subway expansion). In addition, we control for spatial effects explicitly by employing Bayesian multilevel binary logistic models with spatial random effects. Multilevel models are useful in capturing spatial heterogeneity exiting in the vertical-geographic scale direction (i.e., varying intercept), but cannot reflect the horizontal spatial autocorrelation. To resolve this issue, we employ a conditional autoregressive model (*CAR* model) to specify spatial random effects[2]. Non-informative priors are used for all estimates and all continuous variables are standardized. Our model can be written as follows:

$$\Pr\left(y_i = 1 \middle| X_{SD,} X_{Year,} X_{BE}\right) = \alpha_{j[i]} + s_{j[i]} + \beta_{SD}^{\intercal} X_{SDi} + \beta_{Year} X_{Yeari}$$
$$\alpha_j \sim N(\gamma + \gamma_{BE}^{\intercal} X_{BEj}, \sigma_\alpha^2)$$
$$s_j \sim N\left(\overline{s_j}, \frac{\sigma_s^2}{n_j}\right) \qquad (2)$$
$$\overline{s_j} = \sum_{k \in neighborhoods(j)} w_{j,k} s_k / n_j$$

where $y$ indicates commuting modes (i.e., subway, automobile and other modes including bus, walk and bicycle) and $X_{SD}, X_{Year}\ and\ X_{BE}$ represent socio-demographics, year (1=2009 and 0=2005) and built environment factors, respectively. Built environment factors are measured at the neighborhood level (jie dao) and treated as group level variables because people living in the same neighborhood have the same value. $w_{j,k}$ refers to the weight between neighborhoods $j$ and $k$ (1 if they share boundaries and 0 otherwise) and $n_j$ represents the number of adjacent neighbors only. $\alpha_j$ is the varying intercept and $s_j$ represents spatial random effects.

Second, we specify a dynamic model to examine the relationship between the subway system expansion and commuting behavior with only 2009 observations. Specifically, our analyses include the change in the number of subway stations (1 = increased number of subway stations after the expansion; 0=no change) and the interaction between the number of subway stations in 2005 and the change in the number of subway stations. This will allow us to consider the level of subway accessibility in 2005 and its connection with the new subway system expansion. In addition, we are aware of the potential self-selection issue. For example, people might move into the treated neighborhood (i.e., areas with the new subway expansion) before the opening of new subway lines because they prefer subway for their commuting mode. In this case, movers in the treated neighborhoods presumably are more likely to use subway than non-movers. Recent studies suggested that the residential self-selection issue in the Chinese city context should not be treated as serious as it seems in the developed countries due to the institutional constraints in housing markets (Wang and Lin, 2014). We partly control for this concern by using a *Mover* dummy variable based on the 2009 survey. It implies those who have experienced residential relocations over the past five years. The model can be expressed as below:

$$\Pr\left(y_i = 1 \middle| X_{SD,} X_{Mover,} X_{BE,} X_{Station2005}, X\right.$$

$$\omega_j \sim N(\zeta + \zeta_{BE}^{\intercal} X_{BEj} + \zeta_{Station} X_{Station2005j} + \zeta$$

statistical inference. Interestingly, additional analyses show that the estimates from the multilevel models with/without spatial random effects are very similar. The results still show very significant associations between *Year* and subway and other modes uses, indicating the potential impacts of the new subway system expansion on different mode choices.

[Table 3 here]

The Deviance Information Criterion (DIC) is often used to compare the performance of different Bayesian models. In general, complex models will fit the data better than simple models. This measure considers not only the goodness of fit but also the complexity of model to resolve this issue. DIC values from the multilevel binary logistic models with spatial random effects are much smaller than those from the traditional binary logistic models, showing the better performance.

So far we have examined the static impact of the new subway system expansion on commuting mode choice. However, this model setup ignores the changes in the number of subway stations across neighborhoods between 2005 and 2009. Table 4 shows how the change in the number of subway stations at each neighborhood in 2009 influences residents' commuting mode choices.

[Table 4 here]

As shown in Table 4, the number of subway stations in 2005 is positively related with the subway use however, its association is not significant at the 0.05 level of significance. Additional analysis shows that this association becomes very significant if the traditional binary logistic model is employed, confirming the importance of considering spatial effects. We find no significant difference in the residents' commuting mode choice between affected areas (areas that experienced the subway system expansion in 2009) and unaffected areas across different model specifications. In addition, interaction between the number of subway stations in 2005 and the change in the number of subway stations is not statistically significant for all models. This implies that the association between the new subway system expansion and mode choice is not related to the basic level of subway accessibility before the investment. The model specification would make more sense if the dependent variable is the change in subway use for the same person or area. We aggregated data at the neighborhood level and examined the relationship between the changes in the percentage of subway uses and the changes in subway station numbers before and after the new subway expansion, and found very similar results. Finally, the results show that movers are more likely to use subway for commuting but less likely to use other modes than non-movers living in the same neighborhood. This implies that the subway system improvement in certain areas could result in the influx of new population in those areas who would like to use subway.

## 5 Conclusion

This paper examines the effects of new subway infrastructure expansion on commuting behavior in Beijing, China. A comparison between traditional binary logistic models and

Bayesian multilevel logistic models yields several useful insights in the commuting behavior analysis.

First, we find the displacement effect of commuting patterns from other low-carbon transportation modes (walk, bicycle and bus) to subway but not from private cars. That is, our results show a significant rise in subway commuting trips in 2009 compared to 2005 while non-motorized and bus commuting trips are reduced. One possible interpretation of these results is that subway system investments may not suffice for influencing car commuting mode choice due to the prevailing socio-demographics and built environment constraints. Another potential explanation is that once a person owns a car, s/he may like to drive to work even though the subway system is improved. In terms of policy implications, these result suggest that the subway system expansion may not be necessarily associated with the reduction in energy use and transportation emissions via commuting behavioral changes. Second, our results show a positive association between the level of subway station accessibility and subway use. That is, people living in neighbourhoods with a good subway system are more likely to use subway than those residing in areas with a poor subway system. However, this association becomes insignificant when the spatial effects are considered. The results also show an insignificant association between the change in the number of subway stations and subway use, indicating that the current subway expansion produces unsatisfactory results. Third, we find evidence that movers are more likely to use subway for commuting compared to non-movers, implying the influx of new people due to the subway system expansion.

Some limitations of this study deserve a further investigation. First, the surveys employed here are not the individual panel data. We are not able to use the panel regression techniques to resolve the potential concerns relating to unobserved factors that may affect people's commuting mode choice over time. Furthermore, the timing of the second survey may not be sufficiently long enough to capture the effects of the new subway system investments. Third, income category in our data is somewhat arbitrarily. Residents' income levels are related to the job position and working schedule. In addition, high-income people will have more flexible working hours and require more flexibility on travelling. Future work are encouraged to pursue these areas.

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## References

Besser, L. M., & Dannenberg, A. L. (2005). Walking to Public Transit: Steps to Help Meet Physical Activity Recommendations. American Journal of Preventive Medicine, 29, 273-280.

Bhat, C. R. (2000). A multilevel cross-classified model for discrete response variables. Transportation Research Part B, 34, 567-582.

Boarnet, M.G., Crane, R. (2001). The influence of land use on travel behavior: specification and estimation strategies. Transportation Research Part A, 35(9), 823–845.

Bottai, M., Salvati, N., Orsini, N. (2006). Multilevel models for analyzing people's daily movement behavior. Journal of Geographical System, 8(1), 97–108.

Cao, X. J., & Schoner, J. (2014). The influence of light rail transit on transit use: An exploration of station area residents along the Hiawatha line in Minneapolis. Transportation Research Part A, 59, 134–143.

Cao, X., Mokhtarian, P. L., & Handy, S. L. (2009). Examining the impacts of residential self-selection on travel behaviour: A focus on empirical findings. Transport Reviews, 29(3), 359–395.

Cao, X., Mokhtarian, P.L., Handy, S.L. (2006). Neighborhood design and vehicle type choice: evidence from Northern California. Transportation Research Part D, 11(2), 133–145.

Cervero, R. & Radisch, C. (1996). Travel choices in pedestrian versus automobile oriented neighborhoods. Transport Policy, 3(3), 127–141.

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

Cervero, R. (1994). Transit-based housing in California: evidence on ridership impacts. Transport Policy, 1(3), 174–183.

Cervero, R., (2002). Built environments and mode choice: toward a normative framework. Transportation Research D, 7 (4), 265–284

Cervero, R., Day, J. (2008). Suburbanization and transit-oriented development in China. Transport Policy, 15(5), 315–323.

Ding, W, Zheng,S, Guo, X. (2010). Value of access to jobs and amenities: Evidence for new residential properties in Beijing. Tsinghua Science and Technology, 15(5), 595–603.

Ewing, R., & Cervero, R. (2010). Travel and built environment, Journal of American Planning Association, 76, 265-294

Harris, R., Dong, G., & Zhang, W. (2013). Using contextualized geographically weighted regression to model the spatial heterogeneity of land prices in Beijing, China. Transactions in GIS, 17(6), 901-919

Handy, S., Cao, X., Mokhtarian, P., (2005). Correlation or causality between the built environment and travel behaviour? Evidence from Northern California. Transportation Research Part D, 10, 427–444

Hong, J & Goodchild, A (2014). Land use policies and transport emissions: modeling the impact of trip speed, vehicle characteristics and residential location, Transportation Research Part D, 26, 47-51.

Hong, J & Shen, Q (2013). Residential density and transportation emissions: examining the connection by addressing spatial autocorrelation and self-selection. Transportation Research Part D, 22, 75-79.

Hong, J., Shen, Q., & Zhang, L. (2014). How do built-environment factors affect travel behavior? A spatial analysis at different geographic scales. Transportation, 41, 419–440.

Litman, T. (2015). *Evaluating Public Transit Benefits and Costs: Best practice guidebook*. Victoria Transport Policy Institute.

Lund, H.M., Cervero, R., Willson, R.W. (2006). A re-evaluation of travel behavior in California's TODs. Journal of Architecture and Planning Research, 23 (3), 247–263.

Mitchell, R.B., Rapkin, C., (1954). *Urban Traffic: A Function of Land Use*. Columbia University Press, New York.

Mokhtarian, P. L., and X. Cao. (2008). Examining the impacts of residential self-selection on travel behavior: A focus on methodologies. Transportation Research Part B, 42(3), 204–228.

Pan, H. X., Q. Shen, and T. Zhao. (2013). Travel and car ownership of residents near new suburban metro stations in Shanghai. Transportation Research Record, 2394, 63–69.

Pan, H., Shen, Q., Zhang, M., (2009). Influence of urban form on travel behaviour in four neighbourhoods of Shanghai. Urban Studies, 46 (2), 275–294.

Peng, Z.R., (1997). The jobs–housing balance and urban commuting. Urban Studies, 34 (8), 1215–1235.

Schabenberger, O. and Gotway, C.A., 2005. *Statistical methods for spatial data analysis.* Texts in statistical science. Boca Raton: Chapman & Hall/CRC.

Schwanen, T., Dieleman, F.M., Dijst, M. (2003). Car use in Netherlands daily urban systems: does polycentrism result in lower commute time? Urban Geography, 24, 410-430.

Shen, Q. (2000). Spatial and social dimensions of commuting. Journal of the American Planning Association, 66(1), 68–82.

Wang, D., & Lin, T. (2014). Residential self-selection, built environment and travel behavior in the Chinese Context. Journal of Transport and Land Use, 5–14.

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

Wang, D., Y. Chai, and F. Li. (2011). Built environment diversities and activity-travel behavior variations in Beijing, China. Journal of Transport Geography, 19(6), 1173–1186.

Wu, W., Dong, G. (2014). Valuing green amenities in a spatial context. Journal of Regional Science, 54, 569-585.

Wu, W., Dong G., Zhang, W. (2015a). The puzzling heterogeneity in amenity capitalization effects on land markets, Papers in Regional Science, online version available. DOI: 10.1111/pirs.12186

Wu,W., Dong, G., & Wang, B. (2015b).Does planning matter? Effects on land markets. Journal of Real Estate Finance and Economics, 50,242–269.

Yang, J., Q. Shen, J. Shen, and C. He. (2012). Transport impacts of clustered development in Beijing: Compact development versus overconcentration, Urban Studies, 49(6), 1315–1331.Zhang, W., Yin, W., Zhang, J., Meng, B. and Gao, X. (2006). A Study of Livable Cities in China (Beijing). Beijing: Social Sciences Academic Press.

Zhao, P. J. (2010). Sustainable urban expansion and transportation in a growing megacity: Consequences of urban sprawl for mobility on the urban fringe of Beijing. Habitat International, 34(2), 236–243.

Zhao, P., (2013). The impact of the built environment on individual workers' commuting behavior in Beijing. International Journal of Sustainable Transportation, 7(5), 389–415.

Zheng, S., & Kahn, M. E. (2013). Does government investment in local public goods spur gentrification? Evidence from Beijing. Real Estate Economics, 41, 1–28.

Zheng, S., Kahn, M.E. (2008). Land and residential property markets in a booming economy: new evidence from Beijing. Journal of Urban Economics, 63, 743–757.

Table 1 Descriptive statistics for 2005 and 2009 survey observations

| | 2005 survey | | 2009 survey | |
|---|---|---|---|---|
| | Mean* | SD | Mean* | SD |
| | | | | |
| Age (1=young adults (AGE<40); 0= middle age and old adults (AGE>=40)) | 67.28% | 0.47 | 71.61% | 0.45 |
| Household size | 2.61 | 1.00 | 2.83 | 0.93 |
| Income 1 (Monthly household income in RMB 100): 30 and less | 25.93% | 0.44 | 13.34% | 0.34 |
| Income 2 (Monthly household income in RMB 100): 31–50 | 38.62% | 0.49 | 27.40% | 0.45 |
| Income 3 (Monthly household income in RMB 100): 51–100 | 27.13% | 0.45 | 40.14% | 0.49 |
| Income 4 (Monthly household income in RMB 100): 101–150 | 5.99% | 0.24 | 13.96% | 0.35 |
| Income 5 (Monthly household income in RMB 100): 151–200 | 1.23% | 0.11 | 3.14% | 0.17 |
| Income 6 (Monthly household income in RMB 100): 200 and above | 1.10% | 0.10 | 2.02% | 0.14 |
| | | | | |
| Employment accessibility (Indicator of weighted employment density, See Ding et al., 2010) | 0.05 | 0.08 | 0.06 | 0.09 |
| Population density (1000 persons per $km^2$) | 2.92 | 4.33 | 2.84 | 4.08 |
| | | | | |
| # of subway stations | 0.66 | 1.13 | 1.25 | 1.52 |
| | | | | |
| Subway (subway=1; otherwise=0) | 7.76% | 0.27 | 12.18% | 0.33 |
| Automobile (private car and taxi=1; otherwise=0) | 12.53% | 0.33 | 16.77% | 0.37 |
| Other modes (bus, bicycle and walk =1; otherwise=0) | 79.71% | 0.40 | 71.05% | 0.45 |
| Sample size | 6440 | | 3022 | |

* represents the percentage for categorical variables

**Table 2 Effects of subway transit improvement on commuting mode choices (Binary logistic model)**

| | Subway | | | Automobile | | | Other modes | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | 95% CI* | | Mean | 95% CI* | | Mean | 95% CI* | |
| | | 2.5% | 97.5% | | 2.5% | 97.5% | | 2.5% | 97.5% |
| Intercept | -3.25 | -3.47 | -3.05 | -2.83 | -3.05 | -2.61 | 2.18 | 2.03 | 2.33 |
| Age (1=young adults) | 0.65 | 0.48 | 0.83 | -0.30 | -0.43 | -0.17 | -0.08 | -0.19 | 0.04 |
| Household size | -0.05 | -0.12 | 0.02 | -0.11 | -0.17 | -0.04 | 0.10 | 0.04 | 0.15 |
| Income2 | 0.30 | 0.11 | 0.50 | 0.67 | 0.44 | 0.89 | -0.53 | -0.68 | -0.37 |
| Income3 | 0.49 | 0.29 | 0.69 | 1.52 | 1.29 | 1.74 | -1.16 | -1.32 | -1.01 |
| Income4 | 0.27 | -0.04 | 0.57 | 2.27 | 2.01 | 2.52 | -1.69 | -1.89 | -1.50 |
| Income5 | 0.60 | 0.12 | 1.09 | 2.35 | 1.99 | 2.69 | -1.90 | -2.23 | -1.57 |
| Income6 | 0.33 | -0.29 | 0.91 | 2.46 | 2.06 | 2.86 | -1.90 | -2.27 | -1.51 |
| Employment accessibility | 0.08 | 0.00 | 0.16 | -0.18 | -0.26 | -0.10 | 0.06 | 0.00 | 0.13 |
| Population density | 0.01 | -0.05 | 0.06 | 0.01 | -0.05 | 0.05 | -0.01 | -0.05 | 0.04 |
| Year | 0.43 | 0.28 | 0.59 | 0.04 | -0.08 | 0.17 | -0.24 | -0.34 | -0.13 |
| DIC | 5687.17 | | | 7048.78 | | | 9686.47 | | |

* If the 95% credible interval (CI) does not include 0, it implies that the estimate is significant at the 0.05 level of significance.

**Table 3 Effects of subway transit improvement on commuting mode choices (multilevel binary logistic regressions with spatial random effects)**

| | Subway | | | Automobile | | | Other modes | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | 95% CI* | | Mean | 95% CI* | | Mean | 95% CI* | |
| | | 2.5% | 97.5% | | 2.5% | 97.5% | | 2.5% | 97.5% |
| Intercept | -3.40 | -3.64 | -3.17 | -2.94 | -3.17 | -2.73 | 2.25 | 2.10 | 2.42 |
| | | | | | | | | | |
| Age (1=young adults) | 0.66 | 0.46 | 0.86 | -0.28 | -0.41 | -0.14 | -0.10 | -0.21 | 0.01 |
| Household size | -0.05 | -0.12 | 0.04 | -0.11 | -0.18 | -0.05 | 0.10 | 0.05 | 0.15 |
| Income2 | 0.28 | 0.07 | 0.50 | 0.68 | 0.45 | 0.92 | -0.52 | -0.68 | -0.36 |
| Income3 | 0.47 | 0.26 | 0.71 | 1.54 | 1.32 | 1.77 | -1.18 | -1.34 | -1.03 |
| Income4 | 0.26 | -0.07 | 0.58 | 2.31 | 2.06 | 2.58 | -1.72 | -1.93 | -1.50 |
| Income5 | 0.55 | -0.03 | 1.07 | 2.37 | 1.97 | 2.74 | -1.91 | -2.24 | -1.58 |
| Income6 | 0.26 | -0.41 | 0.87 | 2.58 | 2.17 | 3.00 | -1.99 | -2.36 | -1.63 |
| | | | | | | | | | |
| Employment accessibility | 0.04 | -0.13 | 0.26 | -0.12 | -0.25 | 0.01 | 0.03 | -0.08 | 0.17 |
| Population density | 0.08 | -0.07 | 0.21 | 0.00 | -0.09 | 0.08 | -0.01 | -0.10 | 0.08 |
| | | | | | | | | | |
| Year | 0.33 | 0.17 | 0.49 | 0.06 | -0.08 | 0.19 | -0.20 | -0.32 | -0.09 |
| $\sigma_\alpha$ | 0.16 | 0.01 | 0.42 | 0.17 | 0.01 | 0.37 | 0.24 | 0.07 | 0.39 |
| $\sigma_s$ | 1.24 | 0.92 | 1.56 | 0.58 | 0.26 | 0.86 | 0.58 | 0.28 | 0.85 |
| DIC | 5419.66 | | | 6961.23 | | | 9507.4 | | |

* If the 95% credible interval (CI) does not include 0, it implies that the estimate is significant at the 0.05 level of significance.

**Table 4 Results from multilevel logistic regression with spatial random effects using the 2009 survey**

| | Subway | | | Automobile | | | Other modes | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | 95% CI* | | Mean | 95% CI* | | Mean | 95% CI* | |
| | | 2.5% | 97.5% | | 2.5% | 97.5% | | 2.5% | 97.5% |
| Intercept | -3.19 | -3.67 | -2.68 | -2.78 | -3.28 | -2.31 | 2.03 | 1.67 | 2.40 |
| Age (1=young adults) | 0.61 | 0.33 | 0.91 | -0.53 | -0.75 | -0.29 | 0.08 | -0.12 | 0.28 |
| Household size | -0.02 | -0.15 | 0.12 | -0.19 | -0.30 | -0.07 | 0.13 | 0.04 | 0.22 |
| Income2 | 0.19 | -0.22 | 0.59 | 0.63 | 0.16 | 1.10 | -0.44 | -0.76 | -0.12 |
| Income3 | 0.45 | 0.07 | 0.86 | 1.40 | 0.98 | 1.87 | -1.08 | -1.40 | -0.77 |
| Income4 | 0.26 | -0.21 | 0.77 | 2.21 | 1.73 | 2.70 | -1.60 | -1.97 | -1.27 |
| Income5 | 0.44 | -0.29 | 1.15 | 2.39 | 1.79 | 3.01 | -1.89 | -2.42 | -1.37 |
| Income6 | 0.27 | -0.65 | 1.16 | 2.63 | 1.89 | 3.35 | -1.99 | -2.61 | -1.37 |
| Employment accessibility | 0.13 | -0.12 | 0.37 | -0.36 | -0.59 | -0.15 | 0.14 | -0.04 | 0.32 |
| Population density | -0.02 | -0.24 | 0.20 | 0.03 | -0.13 | 0.17 | -0.01 | -0.16 | 0.13 |
| Mover | 0.38 | 0.10 | 0.64 | 0.19 | -0.06 | 0.42 | -0.34 | -0.54 | -0.14 |
| # of subway stations in 2005 | 0.17 | -0.07 | 0.38 | 0.07 | -0.09 | 0.24 | -0.04 | -0.21 | 0.12 |
| Change in # of stations (1=Changed) | 0.04 | -0.40 | 0.50 | 0.05 | -0.30 | 0.42 | -0.05 | -0.37 | 0.26 |
| Interaction | 0.01 | -0.39 | 0.42 | -0.13 | -0.45 | 0.17 | -0.06 | -0.36 | 0.23 |
| $\sigma_{\omega}$ | 0.75 | 0.47 | 1.02 | 0.54 | 0.30 | 0.74 | 0.58 | 0.45 | 0.74 |
| $\sigma_{v}$ | 0.65 | 0.14 | 1.35 | 0.34 | 0.03 | 0.99 | 0.21 | 0.02 | 0.62 |
| DIC | | 2107.69 | | | 2491.20 | | | 3400.54 | |

* If the 95% credible interval (CI) does not include 0, it implies that the estimate is significant at the 0.05 level of significance.

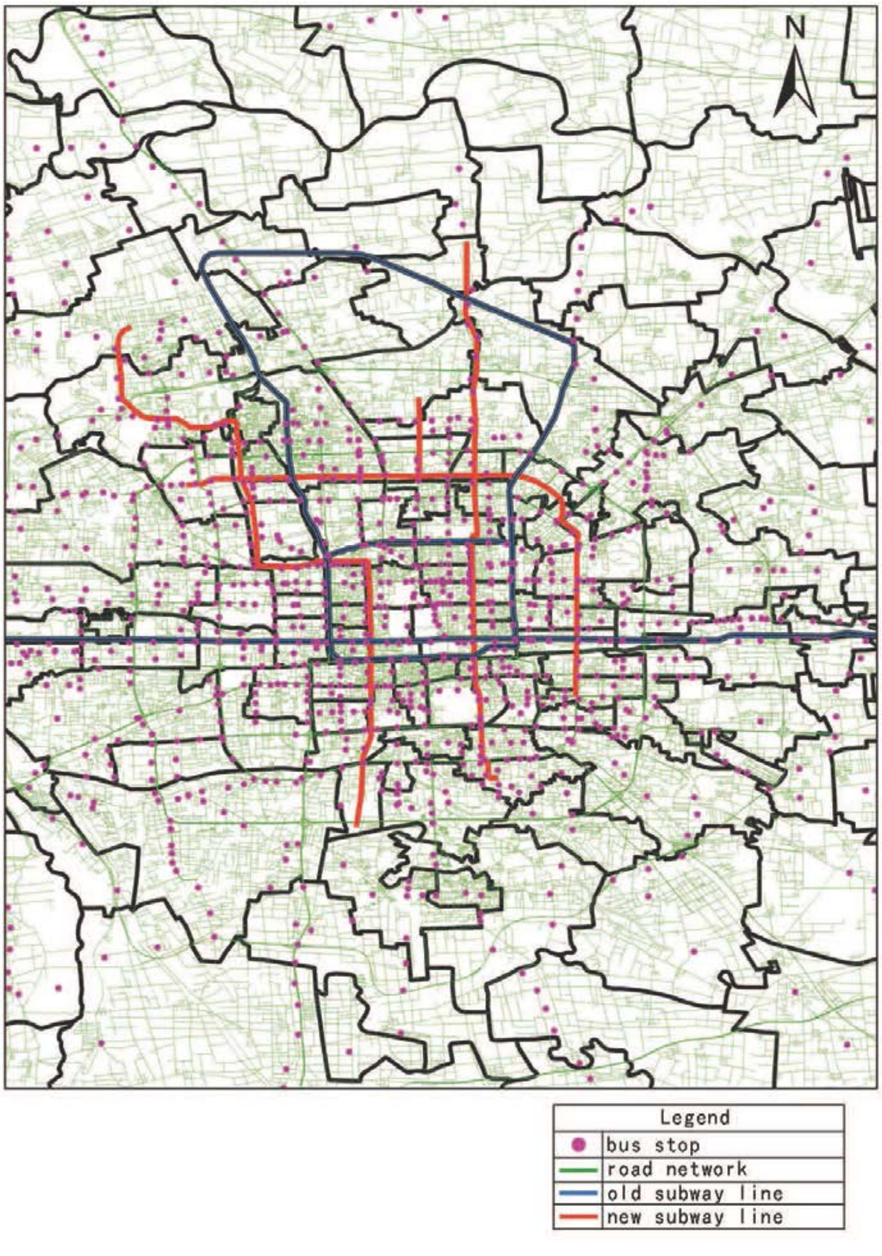


**Figure 1. A sketch map of the subway system, bus stations and road networks in Beijing**