The Economic and Health Impacts of Subway Construction: Evidence from Beijing

Center for Transportation, Environment, and Community Health
Final Report

by
Shanjun Li, Panle Jia Barwick, Andrew Waxman, Jing Wu

October 19, 2018

DISCLAIMER

TECHNICAL REPORT STANDARD TITLE)
PAGE)

1. Report No.	2.Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle The Economic and Health Impacts of Subway Construction: Evidence from Beijing		5. Report Date October 19, 2018 6. Performing Organization Code
7. Author(s) Shanjun Li, Panle Jia Barwick, Andrew Waxman, Jing Wu		8. Performing Organization Report No.
9. Performing Organization Name and Address Cornell University Ithaca, NY 14853		10. Work Unit No. 11. Contract or Grant No. 69A3551747119
12. Sponsoring Agency Name and Address U.S. Department of Transportation 1200 New Jersey Avenue, SE Washington, DC 20590		13. Type of Report and Period Covered Final Report 10/1/2017 – 9/31/2018 14. Sponsoring Agency Code US-DOT
15. Supplementary Notes		

16. Abstract

Project Abstract:

This project aims to understand the large-scale transport infrastructure in the context of subway expansion in Beijing on traffic congestion, air pollution and ultimately on the wellbeing of the residents. The analysis produces estimates of the benefits from congestion relief and air quality from subway expansion and compare them with other transportation policies such as driving restriction and congestion pricing through their impacts on the housing market in Beijing.

17. Key Words	18. Distribution Statement
Subway expansion, air pollution, traffic congestion	The study will be made available on the website of Cornell Institute for China Economic Research at http://China.dyson.cornell.edu.

19. Security Classif (of this report)	20. Security Classif. (of this page)	21. No of Pages	22. Price
Unclassified	Unclassified		

Form DOT F 1700.7 (8-69)

The Economic and Health Impacts of Subway Construction: Evidence from Beijing*

Panle Jia Barwick Shanjun Li Andrew Waxman Jing Wu

October 2018

Abstract

Air pollution and traffic congestion are two of the most pressing urban challenges in many fast-growing economies. Various transportation policies from both the demand and supply sides including congestion pricing, driving restrictions, the gasoline tax, and the expansion of public transit have been adopted to address these issues. We develop and estimate a residential location sorting model to examine the interactions of transportation policies and household sorting. The sorting model incorporate commuting decisions and generates equilibrium predictions of household locations under different transportation policies. We estimate the model parameters using a large household travel survey and rich housing transaction data in Beijing. The analysis illustrates the importance of incorporating travel mode choices in household location decisions and the importance of understanding sorting behavior in designing effective transportation policies.

Keywords: Subway, housing markets, equilibrium sorting, transportation

JEL Classification Codes: H41, R21, R41

*PLEASE DO NOT CITE WITHOUT AUTHOR PERMISSION. Barwick: Department of Economics, Cornell University and NBER (email: panle.barwick@cornell.edu); Li: Dyson School of Applied Economics and Management, Cornell University and NBER (email: sl2448@cornell.edu); Waxman: LBJ School of Public Affairs, University of Texas at Austin (email: awaxman@utexas.edu); Wu: Department of Construction Studies, Tsinghua University (email: ireswujing@tsinghua.edu.cn). We gratefully acknowledge the excellent research assistance of Ziye Zhang and Avralt-od Purevjav. We acknowledge the partial financial support from the International Initiative for Impact Evaluation (3ie) under project DPW1.1106.

1 Introduction

Urban China has been undergoing a subway boom since it announced its bid for the Summer Olympics in 2001. As part of a multi-pronged strategy to address extreme air pollution, traffic congestion and accessibility in the face of rural to urban migration, the Chinese government has dramatically expanded the network of the subway system in its cities, having constructed over 5,000 kilometers of urban rail by 2017 according to the China Urban Rail Transit Association.[1]

This expansion has been paired with several policies intended to disincentivize car travel: driving restrictions by day, a lottery to be able to purchase a vehicle, and increases in gasoline taxes. While much has been made about the ability of the Chinese government to undertake ambitious policy agendas that may be politically infeasible elsewhere (an example of which is its carbon market launched in 2017), the approach to transportation is conspicuous given what is generally known about the success of the aforementioned policies. Davis (2008), Viard and Fu (2015) and Zhang et al. (2017) have shown that driving restriction policies are largely unsuccessful and Li (2017) shows significant misallocation costs of the use of a lottery system to restrict vehicle purchases.

This is all the more serious given the extent of pollution and congestion problems in Beijing. As shown in Figure 1, Beijing has seem a 55% increase in population a 300% increase in income, and a 500% increase in vehicle registrations making it one of the most polluted and congested cities in the world. Given the evidence that restriction policies are not (cost) effective we want to ask what the consequences of this non-optimal policy environment are and how overlapping policies interact and what their distributional consequences are. Estimating these effects is particularly challenging in urban markets where general equilibrium effects are strong.

To begin to address these issues, we seek in this study to understand how various transportation policies affect household location decisions and housing prices. Since housing and transportation markets feature endogenous prices, we also would like to know how household sorting and commuting decisions affect equilibrium housing price and road congestion levels. While the former has been well studied in the residential sorting literature, most studies of housing location take congestion to be exogenous. We also wish to link these to the effects across Beijing on heterogeneous households.

To address these questions, we estimate a household-level structural model of residential location sorting based on commuting. We utilize a rich transaction-level housing data for Beijing that identifies home and work location. In our model, house choice embeds commuting options for work. We account for these options by separately estimating a mode choice model from the Beijing Household Travel Survey (BHTS). Our model incorporates preference heterogeneity and allows for general equilibrium feedback effects between housing and commuting. We use the model and esti-

[1] See http://www.railjournal.com/index.php/asia/chinese-urban-rail-reaches-5000km.html for a discussion.

mates to conduct counterfactual policy simulations for what Beijing would look like in the absence of its transportation policies and also with alternative policies. Unsurprisingly, our main finding reveals that these policies induce relocation: when driving is not an option, the rich outbid the poor near public transit locations.

This paper makes intends to make a contribution to the equilibrium housing sorting literature, which seeks to uncover the willingness-to-pay for non-market amenities and then simulate policy impacts of changes in those amenities. These models rely on the principle that households choose housing based, in part, on the location. The importance of a location depends on the proximity to local public goods (parks, schools, clean air), negative externalities (pollution, crime) and the characteristics of other residents of the neighborhood (race, income, education, housing quality). It is the aggregation of individual choices that results in the aggregate levels of these attributes, which presents a fundamental challenge to identify individual willingness-to-pay for them. These equilibrium sorting models use the properties of market equilibria, together with information on household behavior, to infer structural parameters that characterize preference heterogeneity.

While this literature is fairly broad, we believe the two papers closest to what we do here are Kuminoff (2012) and Rhode and Strumpf (2003), who similarly incorporate considerations of work location commuting into a choice of housing location. While both papers focus on the US, we also believe that we are able to, given our data, construct a more extensive analysis of the role of commuting in housing choice, which allows us to perform the type of simulation exercises that those papers do not.

Our paper relates to another broader literature trying to understand the effects of policies that attempt to address negative externalities associated with vehicle usage. These studies have focused on a host of policies including gasoline taxes (Parry and Small (2005); Bento et al. (2009); Knittel and Sandler (2013); Li et al. (2014)), public transit subsidies and expansion (Parry and Small (2009); Duranton and Turner (2011); Anderson (2014); Yang et al. (2018b)). A final related literature considers the affect of transportation system on property values and spatial distribution (Baum-Snow and Kahn (2000); Gibbons and Machin (2005); Zheng and Kahn (2013); Li et al. (2016); Klaiber and Smith (2010)). While these studies are important and reveal much about individual responses to transportation, they cannot answer the larger scale policy questions posited here about how housing and transportation markets *as a whole* respond to these policies.

We proceed in the next section of the paper to elaborate the policy background for transportation in Beijing. We propose a stylized theoretical explanation of sorting of heterogeneous groups due to transportation technology in Section 3. Section 4 describes the data used in this study, while Section 5 lays out our econometric framework. The results of that framework are provided in Section 6 and in Section 7 we use those estimates to simulate a series of transportation policies and evaluate their welfare consequences. Section 8 concludes.

2 Policy Background

The central government of China as well as regional and municipal governments have pursued a series of policies to address concerns with the transportation system. Although it has never been implemented, road pricing in Beijing has been considered since at least 2015. Instead of pricing, the government has had a gasoline tax since 2009 that it has gradually been increasing from 0.4 to 1.4 RMB. It limits the purchase of cars through both a 10% sales tax instituted in 2001 and a vehicle purchase restriction initiated in 2011. The restriction policy sets a limit on the number of new vehicle purchase licenses, which was initially 250,000, but was reduced to 100,000 in 2018.

Of interest for our study, the government initiated a driving restriction policy in Beijing starting in 2008 which restricted private vehicle owners from driving within the 5th ring road of the city during one day of the week based upon the vehicle's license plate. The policy entails a fine of roughly $30 and is enforced by a camera system. In addition, as mentioned earlier, the government has expanded the subway network tremendously the network was initially set up with two lines and 31 stations in 2002, but as of 2018 it has expanded to 21 lines and 370 stations corresponding to 609 kilometers of rack. While there is some evidence that the subway boom may be decelerating, the government projects subway development to reach 999km by 2021.[2] Subway operation is highly subsidized with a base fare of 2 RMB ($0.30) per trip.

3 Theoretical Underpinnings

We begin by motivating our setup with a monocentric city model to illustrate the mechanisms by which heterogeneous households sort into different locations in response to changes in cost of transportation. The exposition below follows a setup in the spirit of LeRoy and Sonstelie (1983), where a full formal analysis can be found. Here we consider a linear city with boundary at $\bar{r}$. All jobs are at the urban center (CBD), the rest of urban space is housing and we have a closed city where urban population is fixed. Housing supply is fixed and all households rent. Households commute distance r to work with per unit commuting costs t, which include time and pecuniary costs per kilometer. Households choose location and housing quantity to maximize utility given house price, p and income y:[3]

$$\begin{aligned} &\max_{r,h} \quad U(c, h(r)) &&(1)\\ &\text{s.t.} \quad c + p \cdot h(r) = y - t \cdot r. \end{aligned}$$

[2] https://www.citylab.com/transportation/2018/02/chinas-subway-boom-slows-down/552935/

[3] A choice of housing and a location then directly implies a quantity of consumption of the numeraire good, c.

Given a mass of households n residing and working in the city, we can define a spatial equilibrium by a by a bid-rent function which yields a market price for housing consumption unit, $R(r)$, at each distance r from the CBD.[4] An example bid-rent gradient can be found in panel a) of Figure 1. This bid rent function results in prices such that consumers are equally well off at all locations, obtaining indirect utility $V(R(r))$ such that

$$U(c, h^*(r)) = V(R(r)) = \bar{U} \quad \text{for all}\, r \in [0, \bar{r}].$$

Here t corresponds to marginal commuting costs per kilometer ($t \equiv MCC$), which includes pecuniary costs per mile as well as the value of time lost while commuting. A simple parameterization of MCC is $MCC = \delta \cdot wage + \tau$, where $wage$ is the individual's hourly wage, and τ are the pecuniary costs of commuting per km depending on travel mode (e.g., average fare for bus, gasoline and wear and tear for own-car). δ therefore reflects both what share of the hourly wage an individuals values commuting time at and the conversion of commuting time into commuting distance cost.[5]

3.1 Heterogeneity

To understand how this framework affects the location choice of households with different characteristics, note first that to the extent that any two groups have different preferences or endowments, their bid-rent functions can similarly differ. Second, it is helpful to note that because the market clears by allocating housing to the highest bid-rent function at a location, where bid-rent function cross, there will be a change in the type of household that lives on either side of the crossing. Third, at any crossing point, the bid-rent curve with the steeper slope will have its type located to the left of the point and the other type to the right. This can be seen in panels b) and c) of Figure 1. Note further that $R'(r) = -\frac{MCC}{h(r)}$. The simplest possible version of heterogeneity would be of two income types, high (H) and low income (L): $y_H > y_L$. If land consumption of each group is fixed at $h_H(r) = \bar{h}_H$ and $h_L(r) = \bar{h}_L$ and marginal commuting costs are fixed at MCC_H and MCC_L, then low

[4]The bid rent function comes directly from the willingness to pay at every location r from the CBD for a given household, where the household with highest WTP has a winning "bid" and therefore consumes housing at that location with the market price equal to its "bid". This can be seen directly from solving for housing price from the budget constraint, where the bid-rent function's negative slope can be seen from taking the first derivative which is negative:

$$R^*(r) \equiv \max_{h,r} \left\{ \frac{1}{h(r)} [y - c - tr] \right\}.$$

[5]In unconstrained commuting conditions, travel times can be converted into distance using average speed. With congestion, then this involves inverting a non-linear function $Traveltime = f(traveldistance)$.

income households live closer to the CBD in equilibrium if:

$$\frac{MCC_H}{\bar{h}_H} < \frac{MCC_L}{\bar{h}_L}. \tag{2}$$

This relationship is tied directly to two parameters of interest for our study, the income elasticity of marginal commuting costs $\varepsilon_{MCC,y} = \frac{y}{MCC}\frac{\partial MCC}{\partial y}$ and the income elasticity of housing demand $\varepsilon_{h,y} = \frac{y}{h}\frac{\partial h}{\partial y}$. Moreover, if (2) holds, then $\varepsilon_{h,y} > \varepsilon_{MCC,y}$, that is the poor live in the center of the city of the income elasticity of housing is larger than that of marginal commuting costs.[6] The outcome of this can be seen in panel c) of Figure 1, where in this simple example, the relative magnitude of these two income elasticities determines the spatial pattern of residential locations.

We can greater generalize this model by introducing commuting technology that varies in time and pecuniary costs. Suppose one technology, bus, has high marginal costs associated with time while the other, driving one's own car, does not. To the extent that fixed costs of both modes are affordable to individuals, then sorting will occur in a manner analogous to income, because $\frac{MCC_{car}}{\bar{h}} < \frac{MCC_{bus}}{\bar{h}}$, with bus commuters living closer to the CBD.

Combining heterogeneity in commuting with heterogeneity in income further complicates our framework, since the spatial configuration of households may now depend both on relative housing demand, marginal commuting costs differences and ability to pay fixed costs of each mode by incomes of different households. As shown in LeRoy and Sonstelie (1983), as a high fixed cost mode like own-car driving becomes affordable to high and then low income households, we would expect the ordering of bid-rent functions to change and therefore the spatial configuration across income and mode use. For example, panel d) of Figure 1 shows the scenario where car and bus are affordable to both high and low income households, but because marginal commuting costs for a given mode are larger for the high income (because of higher values of time), there is a four ring distribution of households, with high income living the closest to the CBD and commuting by bus, then low income that commute by bus, then high income commuting by car and then low income commuting by car.[7] With this level of complexity it may not strictly possible to solve for the spatial configuration without knowing the bid-rent functions themselves.

The main takeaway of this exposition is that the spatial pattern of residential location depends on two income elasticities: that of housing demand and marginal commuting cost. In the simplest version of the model, when the former is greater than the latter, the poor live in the center of the

[6] If (2) holds, then $\frac{\bar{h}_H}{\bar{h}_L} > \frac{MCC_H}{MCC_L}$. Subtracting one from each side yields $\frac{\bar{h}_H - \bar{h}_L}{\bar{h}_L} > \frac{MCC_H - MCC_L}{MCC_L}$. Multiplying both sides by $\frac{y_L}{y_H - y_L}$ results in a finite difference version of the inequality of elasticities.

[7] It is clear that the relative size of these slopes of these curves implies if MCCs and housing demands are constant within groups that

$$\frac{MCC_{H,bus}}{\bar{h}_{H,bus}} > \frac{MCC_{L,bus}}{\bar{h}_{L,bus}} > \frac{MCC_{H,car}}{\bar{h}_{H,car}} > \frac{MCC_{L,car}}{\bar{h}_{L,car}}.$$

city. With heterogeneous transportation technology, more varied spatial configurations are possible. Though this point has been made based on US data by Glaeser et al. (2008), much of the empirical literature tends to treat MCC as exogenous despite the fact that it is affected by preferences for and the relative costs of different commuting alternatives. In addition the congestion level itself is a function of the urban structure.

Beyond commuting costs, there are many other factors that affect residential location that have been the focus of empirical studies of housing markets and specifically equilibrium sorting models. A survey of this literature is provided by Kuminoff et al. (2013), but includes consideration of the role of school quality (Bayer et al., 2007; Ferreyra, 2007), air quality (Sieg et al., 2004; Bayer et al., 2009; Kuminoff, 2009; Tra, 2010 ; Bayer et al., 2016; Close and Phaneuf, 2017), crime (Bishop and Murphy, 2011) and open space or recreation (Walsh et al., 2007; Timmins and Murdock, 2007; Klaiber and Phaneuf, 2010). Adding valuation of these amenities into the model from equation (1) could result in a greater range of potential locational outcomes for households as they trade off consumption of housing, commuting costs and proximity to these amenities and has been developed analytically in Brueckner et al. (1999).

4 Data Description

To examine how Beijing households respond to the transportation policies enumerated in Section 2, we construct the most detailed housing and work commute dataset ever used in the context of equilibrium sorting models. This dataset combines household-level mortgage transaction data including complex, unit, borrower and co-signer characteristics for 13,865 households purchasing homes in Beijing over 2008-2014.[8] Critically, this mortgage dataset also includes home and work street addresses, which allows us to identify the implied commute to work for a particular home location and compare it to that for alternative homes in the household's choice set. In order to understand the relative benefit of any particular commute to work, we then match these potential home and work location pairs to choices made by households in a separate travel survey conducted in 2010 in Beijing. We begin first by describing this data.

4.1 2010 Beijing Household Travel Survey

We utilize the Beijing Household Travel Survey (BHTS) for observations based on data collected in September and October 2010 by the Beijing Transportation Research Center (BTRC), an agency of the Beijing municipal government. The BTRC has conducted annual household travel surveys

[8]Residences within Chinese cities are predominantly within housing complexes (as is the case for all of our data) much the same as condominiums in the United States.

for many years, and the Beijing municipal government uses these surveys to understand Beijing residents' travel behavior and to inform transportation policies. Academic researchers have also used the survey data to analyze transportation in Beijing ((Wang et al., 2014)).

The BHTS comes from a multistage sampling of households in Beijing in 2010 . BTRC randomly selects a subset of Traffic Analysis Zones (TAZs) from the 1,911 in the entire city. TAZs are geocoded areas about 1.5 square kilometers, on average, although their size also depends on the density of trip origins and destinations, which smaller TAZs located closer to the center of Beijing reflecting the greater density of employment, housing and commercial retail there. The survey covered 46,900 households, 116,142 individuals, and 253,481 trips.[9]. Panel (a) of Figure 3 shows the set of TAZs sampled for the 2010 BHTS with the core of urban Beijing and outside of it. We only consider households living within the 6th ring road, which corresponds to most of urban Beijing.

Each record in the travel survey reflects a single home-to-work or work-to-home trip for a household using a certain commuting mode or modes and records the TAZ of the origin and destination locations. For the purposes of the estimation detailed in Section 5, we need to construct counterfactual trips to understand the characteristics of the trip had it been taken using an alternative mode. We use the centroid of the TAZ from the origin and destination of each location and then calculate travel times and distances by submitting the corresponding latitude and longitude to Google Maps' Application Program Interface (API) server for processing.[10].

In principle, there are a large number of possible modes or mode combinations that any commuter could travel on between home and work. To focus on modes which we observe with regularity in the data and to make the choice modeling described in Section 5 tractable, we keep only travel survey observations for trips where there is a single mode and it is either Driving, Subway, Bus, Walking, or Biking, which is the bulk of all trips in the data.[11] Calculating time and distance for the subway using Google Maps is complicated by the fact that the API is unable to simulate the transit network as far back in the past as 2010. Since the subway network has changed dramatically since then, as discussed in Section 2, and understanding counterfactual travel times and housing choices in the absence of these expansions will be the focus of simulations in section 7, we use an alternative method to calculate subway trip information. First, we assume that households walk to and from the nearest subway station on either end of the subway trip. We then use Geographical Information System (GIS) cartographic data of the subway network extent for the day the trip was

[9]Unfortunately, this approach means that the distance and travel time for trips within a TAZ is necessarily 0 for this method. We drop these trips from the travel survey data.

[10]Submitting a single API request to the Google maps server requires specifying origin and destination latitude and longitude points, a travel mode and a timestamp corresponding to the trip time and date. The API will only process trips for dates up to two weeks into the future, but not in the past. We use the date and time recorded for each record in the travel survey to construct the time stamp for the request.

[11]To limit the effect of measurement error in over- or under-predict the chosen mode, we use distance and time from Google Maps API for both the chosen and unchosen alternatives.

taken to estimate the travel distance and time between the stations nearest to origin and destination.

To estimate the model described below, we construct two attributes of each possible trip, pecuniary and time costs. The former (0.75 RMB/km) is constructed for driving based on the cost of gasoline and average fuel economy in Beijing in 2010. Based on the data about fares in the travel survey, the average cost of a subway trip is 2RMB. For bus travel, there is a 2RMB base fare, which we then adjust based on expected transfers.footnoteTransfer costs are 0.2 yuan for students, 0 for elderly people, 0.4 yuan for people with public transportation cards, and 1 yuan for people without public transportation cards. Walking and biking are assumed to have zero marginal cost. Time costs are based upon the travel time for the trip reported by the Google Maps API.

Panel A of Table 1 reports summary statistics from the travel survey data. We can see that average income is 64,490 RMB, which is almost twice per capita income reported by the China Statistical Yearbook for 2010 of 33,360 RMB, which reflects the fact that these households are more predominantly in central Beijing, are employed and have a fixed dwelling. It is also noteworthy that less than a third of households sampled own a car. This is roughly what the overall pattern of car ownership in the city is from the statistics reported in Figure 1 from the China Statistical Yearbook.

Turning to Figure 4, we can see the distribution of mode choice and travel times in Beijing from the survey. It is noteworthy that while roughly a third of households own cars, only 15% use them, reflecting that some of the policies discussed above may have disincentivized driving and the fact that the car may be used by a different member of the household. It is also noteworthy how low the share of subway ridership is (5.3%) and how relatively long the trips taken on it are. These long trips may reflect the fact that many of these individuals do not have a car and are commuting longer distances for which biking, walking or bus are even more time consuming.

4.2 Mortgage Dataset

Our second dataset consists of transaction-level data for issued mortgage applicants from the largest mortgage provider in Beijing. The underlying dataset includes 72,144 mortgage transactions from 1995-2014. The coverage varies from year to year, increasing over time. To capture housing demand around the time of Beijing's subway boom and for years where we have sufficient mass of observations, we restrict the sample to 13,865 transactions over 2008-2014.[12] The mortgage data includes information about household attributes including income, age, marital status, residency status (*hukou*), and critically for our analysis, the address of the household's work location. We also no for each purchased property the transaction price, date the mortgage was signed and the street address. We contracted with a Beijing-based company to geocode these home and work addresses to a specific latitude and longitude.

[12] We also remove transactions with missing or zero reported price, with price per square meter less than 5,000 RMB, and with buyers with no reported income.

As discussed below, we will need to use predict commuting times and distances for households in the mortgage dataset to estimate our sorting model. For computational tractability, we construct the choice set of a household in our data based on a random sample of 20 homes from the set of all potential houses a household could choose within a two year window around the date we observe their actual home purchase.[13] For each household, we construct commuting distances and times for each housing choice (potential or actual) to the borrower's workplace. We do this in the Google Maps API based upon regions of Beijing corresponding to the intersection of district boundaries with ring roads. There are 25 of these regions as shown in panel (b) of Figure 3, although those outside the 6th ring road are not used.[14] Because our data report the work location of the principal borrower of the mortgage, when we refer to the household's work location, it is this one, though in principle there may be multiple work locations depending upon the labor supply decisions of any particular household.

To identify mean utility parameters in the estimation described below, it is necessary to have sufficient variation in the share of each alternative. Because a single house is only chosen by a single household in our data, we need to define housing choices in a more aggregate form. Following Tra (2010) and Bayer et al. (2007), we collapse the mortgage observations into housing types with attributes based on mean values of the houses within. A single housing type corresponds to a representative house in a given *jiedao*, roughly a neighborhood, within a two year window. Table 1 reports summary statistics from the mortgage data. We can see that household income is even higher reflecting the fact that these households are wealthy enough to purchase a house and qualify for a mortgage. The average distance to work is 10.5km, which is roughly the distance from the center of Beijing to the 3rd ring road, although distances can be as big as 53m, which is a little less than the distance to the 6th ring road. Distances to subways are about half as far away on average, but can also be quite far for households living in outlying areas.

5 Estimation Framework

In this section we lay out the components of a two-stage model to estimate the demand for housing based, in part, on the commuting options available to a given household in that housing location. Building on the model presented in Section 3, we assume that households choose a house based on their preference for housing attributes, commuting alternatives, and neighborhood amenities. The aggregation of individual choices affects the supply of amenities such as pollution, congestion and public education, and controlling for the endogenous formation of these amenities has proven

[13]Estimation using choice-based sampling in random utility models can approximate the true parameters following McFadden (1978).

[14]Ideally we would be able to recalculate travel times and distances for each work location and sampled house across all five possible modes, however this was practical given the limitations of making requests to the API server.

important in estimating household sorting models (Bayer and Timmins, 2005). The equilibrium sorting model presented here characterizes these processes and recovers the underlying housing consumption preferences from choice data.

The choice of a housing location based upon commuting patterns is one part of a joint decision of work and home location choice. The choice of these locations may be simultaneous or sequential, but it is likely that the levels of endogenous amenities will affect both choices following Rosen (1979) and Roback (1982). Because for many households the choice of work location is likely to be the outcome of a longer-term process of labor supply and migration decisions, we take it as given for the purpose of our model. Therefore we define our model as a housing location model within which is nested the expected value of all potential commuting options at that location. Because we do not observe commuting decisions for households in the mortgage data, our approach is to estimate preferences for mode choice from the travel survey. Then using these estimates, we construct a location- and household-specific measure of the value of commuting options for housing locations in the mortgage data. We lay out the framework for this two-stage model below.

5.1 Housing Demand Model

The indirect utility for a household i choosing to live in housing type j can be written as:

$$\max_{\{j\}} V^i_{j\in J} = \alpha^i \log\left(p_j\right) + X_j\beta^i + \gamma^i EV^i_j + \xi_j + \varepsilon^i_j, \tag{3}$$

where y^i is household income, p_j is the price of housing type j, X_j is a vector of housing type attributes, EV^i_j is expected utility from the possible commuting alternatives, ξ_j is a vector of unobserved attributes, and ε^i_j is Type I Extreme Value error. The marginal utility for each housing attribute can be separated into an individual-specific component and a mean component so that: $\alpha^i = \bar{\alpha} + z_i\alpha$ and $\beta^i_k = \bar{\beta}_k + z_i\beta^k$, where z^i are household demographics. Reflecting the fact that the marginal disutility of housing prices is dependent upon income, we estimate our model with specifications that replace $\log\left(p_j\right)$ with $\log\left(\frac{p_j}{y_i}\right)$. In addition, as discussed below, because household i's commuting decision depends on the location of housing type j, the term EV^i_j will vary based upon the work and home location of every household-housing type pair.

5.2 Mode Choice Model

For commuting, which represents derived demand from household labor supply decisions (as well as other time allocation decisions such as leisure, home work and travel), the most salient characteristics of utility-maximizing households in weighing commuting options is their time and financial costs.[15] To reflect these costs, we consider the choice of mode m (among those available for commuter c in location j: M_j^c) by commuter c living at housing location j as:

$$\max_{\{m \in M_j^c\}} v_{jm}^c = \theta_{jm} + \gamma_1 time_{jm}^c + \gamma_2 cost_{jm}^c / y^c + \eta_m z_c + \varepsilon_{jm}^c$$

where θ_{jm} is a mode-specific fixed effect, and $\theta_{j,walk}$ normalized to zero. This fixed efect incorporates mode-specific amenities, disamenities, scheduling or inconvenience costs that do not scale with the time or distance traveled. $time_{jm}^c$ is the time of commuting from housing type j to work using mode m, $cost_{jm}^c$ is the monetary cost for that trip, y^c is the income of commuter c, and ε_{jm}^c is Type I Extreme Value error. A convenient property of the functional form assumed here is that it allows the financial burden to scale with income and it provides a straightforward means to calculate the value of time (VOT) as: $\frac{\gamma_1}{\gamma_2} \cdot y^c$. Estimating this model on the travel survey data produces parameter set $\hat{\Theta} = \left\{ \{\hat{\theta}_j\}_{j=1}^J, \hat{\gamma}_1, \hat{\gamma}_1 \right\}$, where $\hat{\theta}_j = \{\theta_{jm}\}_{m=1}^{M_j}$. We then use these estimates to construct the logsum form of expected utility for all commuting alternatives using time, cost and income data for households i from the mortgage data based on the home and work locations for a given home choice:

$$EV_j^i = \log \left(\sum_{m \in M_j^i} \exp \left[\hat{\theta}_{jm} + \hat{\gamma}_1 time_{jm}^i + \hat{\gamma}_2 cost_{jm}^i / y^i + \eta_m z_i \right] \right). \tag{4}$$

While the application of this two-stage approach to residential sorting and commuting is, to our knowledge, similar approaches of nesting logsum values from random utility models have been executed by Phaneuf et al. (2008) and Capps et al. (2003).

5.3 Model Closing

The identification of the structural parameters of our model relies on our demand equations conforming to the closing conditions of an equilibrium model of location sorting. These conditions are that 1) The housing market clears: the supply is fixed and housing prices adjust to clear the market; 2) Travel times for driving respond to travel demand by car via the empirical relationship between speed and flow across roads in Beijing;[16] 3) The level of congestion affects individual mode choices which then affect the traffic density on the road, 4) Housing prices and traffic con-

[15] Preferences for particular attributes of commuting modes may matter as well such as the enjoyment of driving a car, perceived “greenness” of using public transportation, or health benefits of biking or walking. We include mode-specific fixed effects in the model below to account for these.

[16] We allow travel times to adjust following estimates between travel times and highway density for Beijing reported by Yang et al. (2018a) from a regression of changes in speed on changes in the density of vehicles on roads: Δspeed = ε Δdensity, $\varepsilon = -1.1$.

gestion are determined endogenously in the model.

5.4 Estimation

To obtain the parameters enumerated in the previous section, we begin by estimating the mode choice model via maximum likelihood estimation to recover consumer preference for travel time and cost. We then construct the logsum value $EV_j^i, \forall j \in M_j$ to be used as an observed housing type attribute (specific to i due to work location) as discussed above. We then estimate the location choice model given the following formulation:

$$V_j^i = \mu_j^i(\theta_2) + \delta_j(\theta_1) + \varepsilon_j^i \tag{5}$$

$$\mu_j^i(\theta_2) = \log \;\; p_j \;\; z_i\alpha + \sum_k X_{jk} z_i \beta^k \tag{6}$$

$$\delta_j(\theta_1) = \bar{\alpha} \log \;\; p_j \;\; + X_j \bar{\beta} + \xi_j. \tag{7}$$

The parameters of the model are estimated in two steps following: first, we estimate household-specific parameters (θ_2) and alternative specific constants or mean utilities (δ_j) using maximum likelihood estimation with a nested contraction mapping by matching observed and predicted market shares via the mean utility obtained by inverting shares on each iteration d:

$$\delta_j^{d+1} = \delta_j^d + \ln S_j - \ln s_j \left(\delta_j^d ; \theta_2 \right),$$

where S_j are observed market shares for each housing type and s_j are predicted shares constructed by calculating:

$$\ln s_j \left(\delta_j^d ; \theta_2 \right) = \frac{\exp \;\; V \;\; \delta_j ; \theta_2}{\sum_k \exp\{V\left(\delta_k ; \theta_2\right)\}}.$$

In the second stage, we estimate mean preference parameters (θ_1) in mean utilities via OLS and IV.

5.5 Identification

A couple of factors could potentially confound our estimation of the parameters outlined above, so here we lay out our approach to account for this. First, we include house fixed effects (mean utilities), which control for local-specific unobservables and common shocks that could affect traffic conditions. Second, as discussed above, housing prices and the congestion level are determined simultaneously together with individual mode and location choices. Estimation of (7) is therefore confounded by the fact that this simultaneity means that $E \;\; \xi_j p_j \;\; \neq 0$. To account for this, we instrument for prices using the average attributes of houses (excluding price and the logsum term) between 1-5 kilometers following Berry et al. (1995).

6 Estimation Results

We now lay out the first estimates of demand for housing based on commuting availability for Beijing. We begin by presenting estimation results for the mode choice model. Based on the parameters from that model, we then construct the logsum expected value of commuting options based on place of work and home location for households and estimate their housing demand.

6.1 Mode Choice

In Table 2, we present estimates from a multinomial logit model of mode choice over walking, biking, driving, subway and bus. We include alternative specific constants for each mode except walking, and include additional controls from columns (1)-(4). Comparing columns (1) to (2)-(4) in panel A, it is clear that the estimates change substantially when trip distance is included as a control. Including it makes the coefficient for pecuniary cost negative, which is consistent with intuition. Because the attractiveness of a particular mode will depend upon the length of the trip, if we do not control for this, it may be the case that we are picking up the fact that modes for which there is higher cost (driving, but also subway and bus) are going to be more attractive for longer trips. Once this is included, he results remain fairly consistent as we add respondent (age, sex, education) and household characteristics (size, cars, workers).

In panel B, we then enumerate the implied value of time by taking the ratio of time and cost coefficients from our preferred specification in column (4) of panel A.[17].

6.2 Housing Location Choice

We now turn to the results of estimating the two-stage residential sorting model described in Section 5.2 which utilize estimates from the mode choice model to construct the logsum expected value of commuting options for a household at a given location. Panel A of Table 3 reports the first stage estimates of a maximum likelihood model using a sampling of 20 available properties (plus the chosen one) to construct the choice set. In column (1), we report our preferred estimates, which have a negative sign on the housing price as would square with intuition and a postive sign on the logsum, suggesting that in locations with better commuting options households are more likely to locate there. When we run the same estimation without the logsum, however, we can see that the housing price becomes more negative.

Turning to the second stage, we can see that OLS estimates in columns (1) and (2) seem to underestimate the price coefficient relative to the IV model, suggesting that unobserved housing

[17]These estimates imply a value of time that is 57% of a worker's hourly wage, which is in line with what much of the transportation literature has found (Small (2012))

attributes may upwardly bias our OLS estimates. The coefficient on distance to the city center is consistent with declining pricing gradients moving out from the city center. Higher unit sizes have seem to increase the probability a house is chosen, but looking back at panel A, this increases with a buyer's age, perhaps because for households that eventually have a child or family members live with them.

7 Counterfactual Simulations

We now utilize the estimates from our model of household and mode choice to consider three policy scenarios that help to understand how the series of transportation policies enacted in Beijing have affected households and also benchmark them against a policy that would charge a congestion fee to drive on the road. Specifically, we construct simulations of three alternatives: household behavior in the absence of Driving Restriction Policy (Counterfactual), cordon-style congestion charge within 5th Ring Road and the expansion of subway from 2008 to 2014 network.

7.1 Simulation Approach

In order to simulate these alternative policy scenarios, we alter the inputs to the logsum equation (4) and as a result also for the indirect utility for housing from equation (7). We focus on observations in the last year of our sample, 2014. To simulate the absence of a driving restriction, we replace the alternative specific constant for driving for travel survey respondents inside of the driving restriction area (5th ring road) with those outside of it reflecting the fact that driving is now available to them without penalty. To simulate the effects of expanding the subway network, we replace the times and distances of subway commuting for households based on the same locations from the 2008 subway network. Finally, we consider a 50 RMB congestion cordon within the 5th ring road by increasing the cost of driving for all households with home or work within this road.

For the following simulations, we assume "closed city" with no change in population and a fixed housing supply consisting of the units in our sample. We also assume that the transportation network is fixed apart from the policies described above. The simulation algorithm described below begins with an initial observed price vector and road congestion vector, which will be endogenously determined by the algorithm on each iteration.

After setting the policy vector as defined above, the outer loop of the algorithm allows households to adjust mode choice in response to the policies described. We then reconstruct the logsum based on new travel conditions. Then within an inner loop we allow households to choose a new housing location based on this new logsum expected value. Based upon the new pattern of demand, we resolve for a new price vector that equates housing demand with fixed supply. Given a new pattern of demand we also reconstruct the implied driving in Beijing given mode choice from the inner loop. With that driving pattern, we adjust driving travel times to reflect congestion for driving separately between district-ring road regions. Because transportation policies do not just affect households buying a house (a fraction of all residents), but all commuters, we approximate district-ring road populations and use mode choice probabilities to predict mode switching for these households to construct a new aggregate travel demand pattern for driving D_j [18]

Finally, based on the new driving demand pattern D_{jr}, we then allow driving travel times to respond to the new traffic pattern. Using a speed-density response of -1.1 estimated in Li, Purevjav and Yang, we adjust the implied travel speed and therefore time based upon the number of drivers traveling between district-ring roads regions D_{jr}. We then repeat the inner loop until convergence and then repeat the outer loop until convergence.

7.2 Simulation Results

Table 4 reports the results for simulating the three policy scenarios outlined above while only allowing mode choice (and congestion) to change but not household location. Column (1) reports changes in mode shares and speed for households above and below the median sample income for the counterfactual scenario where there is no driving restriction, no congestion change and no subway expansion. By adding the driving restriction, it is clear that driving becomes less popular, more so above above median income households (having a higher share of car ownership), and speeds raise by roughly 2 kph. The congestion charge also decreases driving, but by less for the Above group as many will still drive but pay the congestion charge. Finally subway expansion disincentivizes driving, increases subway use and decreases the use of some other modes. The effect on speeds is much smaller.

We can compare this with simulations for the same policy scenarios, but where we allow households to also move location. In this case, we can see that under the driving restriction, there is a larger response to the driving restriction, in part because households can move to locations where there ability to not drive is greater, which is consistent with Above households moving closer to the subway and to work. Responses to the congestion charge are also larger for driving, and we can see that this has the effect of allowing Above households to live farther from work and the subway, which may reflect the combination of a desire to live closer to other amenities, consume

[18] Let r be the work district-ring road region for a household, then the total number of drivers traveling from home district-ring road j is $D_{jr} = \hat{d}_{jr} + \Pr[mode_i = drive]_{jr} \cdot d_{jr}^{other}$, where $\hat{d}_{jr}$ is the predicted drivers buying homes and commuting from j to r, and d_{jr}^{other} are non-homebuyers. We calculate the later as $d_{jr}^{other} = \frac{d_{jr}^{travsurvey}}{d_j^{travsurvey}} \cdot d_j^{Beijing}0$, which applies the share of households in the travel survey traveling to r from j to the population that lives in region j. We approximate the latter by overlaying population estimates by *jiedao* (neighborhood) and overlaying this on district-ring road regions.

more housing and pay the toll to drive a slightly longer distance. The subway expansion in column (4) has the effect of dramatically decreasing the distance to the subway for Above households, but not for Below, suggesting sorting as the former displaces the latter in locations around subways.

In Figure 5, we plot price gradients from both sets of simulations with distance from the nearest subway. In panel (a), we compare simulations with the 2008 subway network relative to those with the 2014 network. The fact that the former is steeper suggests a greater premium associated with proximity to the network, which may reflect the fact that on average households are closer to a subway under the 2014 network, so the premium would be lower. In panel (b), we compare price gradients under the driving restriction and the congestion charge which prove to be much steeper, reflecting higher demand for proximity to a subway station when driving is relatively costly.

Finally, we report welfare estimates that compare the welfare affects of each policy relative to the no policy baseline allowing for just travel mode and also travel mode and housing sorting. Welfare estimates are based on consumer surplus and do not include revenue recycling or reflect direct costs of enforcing the driving restriction, implementing the congestion charge or paying for subway expansion. Apart from subway expansion, all of the policies lower welfare, for the driving restriction because households would like to drive if they could and for the congestion charge because they do not receive the revenues back. Costs are larger to high income households likely because these are the households that are likely to drive without the policy. For both the driving restriction and the subway expansion, allowing housing location sorting to occur increases welfare because households are able to better adjust to lower costs of commuting and benefits of location. The exception to this seems to be for low income households under the congestion charge, which may reflect affects on the cost of housing.

8 Conclusion

In this study we have collected detailed transaction-level mortgage data about the purchases of households in Beijing combined with travel survey data to estimate preferences for accessible commutes to work across the city over 2008-2014. We then used the estimates from this model to simulate a series of counterfactual policies to assess the effects of Beijing's vehicle restriction policy and public transportation expansion. The economics literature has been strong to point out that both of these approaches may not be cost effective. While it is in the absence of a full accounting for the implementation costs of these policies, we do demonstrate their negative welfare effects and the comparative benefit of pricing roads. Additionally, we demonstrate how equilibrium sorting can result in lower income households being pushed farther away from public transit, lowering their welfare. To the extent that the central government is willing to continue to expand above and below-ground rail lines across Chinese cities, further relocation of households may be likely.

References

Anderson, Michael L, "Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion," *American Economic Review*, 2014, *104* (9), 2763–96.

Baum-Snow, Nathaniel and Matthew E Kahn, "The effects of new public projects to expand urban rail transit," *Journal of Public Economics*, 2000, *77* (2), 241–263.

Bayer, Patrick and Christopher Timmins, "On the equilibrium properties of locational sorting models," *Journal of Urban Economics*, 2005, *57* (3), 462–477.

_ , Fernando Ferreira, and Robert McMillan, "A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, August 2007, *115* (4), 588–638.

_ , Nathaniel Keohane, and Christopher Timmins, "Migration and hedonic valuation: The case of air quality," *Journal of Environmental Economics and Management*, July 2009, *58* (1), 1–14.

_ , Robert McMillan, Alvin Murphy, and Christopher Timmins, "A Dynamic Model of Demand for Houses and Neighborhoods," *Econometrica*, 2016, *84* (3), 893–942.

Bento, Antonio M, Lawrence H Goulder, Mark R Jacobsen, and Roger H Von Haefen, "Distributional and efficiency impacts of increased US gasoline taxes," *American Economic Review*, 2009, *99* (3), 667–99.

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile prices in market equilibrium," *Econometrica: Journal of the Econometric Society*, 1995, pp. 841–890.

Bishop, Kelly C and Alvin D Murphy, "Estimating the willingness to pay to avoid violent crime: A dynamic approach," *American Economic Review*, 2011, *101* (3), 625–29.

Brueckner, Jan K, Jacques-François Thisse, and Yves Zenou, "Why is central Paris rich and downtown Detroit poor?: An amenity-based theory," *European economic review*, 1999, *43* (1), 91–107.

Capps, Cory, David Dranove, and Mark Satterthwaite, "Competition and market power in option demand markets," *RAND Journal of Economics*, 2003, pp. 737–763.

Close, Brett and Daniel J Phaneuf, "Valuation of Local Public Goods: Migration as Revealed Preference for Place," 2017.

Davis, Lucas W., "The Effect of Driving Restrictions on Air Quality in Mexico City," *Journal of Political Economy*, February 2008, *116* (1), 38–81.

Duranton, Gilles and Matthew A Turner, "The fundamental law of road congestion: Evidence from US cities," *American Economic Review*, 2011, *101* (6), 2616–52.

Ferreyra, Maria Marta, “Estimating the effects of private school vouchers in multidistrict economies,” *American Economic Review*, 2007, *97* (3), 789–817.

Gibbons, Stephen and Stephen Machin, “Valuing rail access using transport innovations,” *Journal of urban Economics*, 2005, *57* (1), 148–169.

Glaeser, Edward L, Matthew E Kahn, and Jordan Rappaport, “Why do the poor live in cities? The role of public transportation,” *Journal of urban Economics*, 2008, *63* (1), 1–24.

Klaiber, Allen H. and Daniel J. Phaneuf, “Valuing open space in a residential sorting model of the Twin Cities,” *Journal of Environmental Economics and Management*, September 2010, *60* (2), 57–77.

Klaiber, H. Allen and V. Kerry Smith, “Valuing Incremental Highway Capacity in a Network,” Working Paper 15989, National Bureau of Economic Research May 2010.

Knittel, Christopher R and Ryan Sandler, “The welfare impact of indirect pigouvian taxation: Evidence from transportation,” Technical Report, National Bureau of Economic Research 2013.

Kuminoff, Nicolai V., “Decomposing the structural identification of non-market values,” *Journal of Environmental Economics and Management*, March 2009, *57* (2), 123–139.

Kuminoff, Nicolai V, “Partial identification of preferences in a dual-market sorting equilibrium,” *Working Paper*, 2012.

Kuminoff, Nicolai V., V. Kerry Smith, and Christopher Timmins, “The New Economics of Equilibrium Sorting and Policy Evaluation Using Housing Markets,” *Journal of Economic Literature*, December 2013, *51* (4), 1007–1062.

LeRoy, Stephen F and Jon Sonstelie, “Paradise lost and regained: Transportation innovation, income, and residential location,” *Journal of Urban Economics*, 1983, *13* (1), 67–89.

Li, Shanjun, “Better Lucky Than Rich? Welfare Analysis of Automobile Licence Allocations in Beijing and Shanghai,” *The Review of Economic Studies*, 2017, p. rdx067.

_ , Joshua Linn, and Erich Muehlegger, “Gasoline taxes and consumer behavior,” *American Economic Journal: Economic Policy*, 2014, *6* (4), 302–42.

_ , Jun Yang, Ping Qin, and Shun Chonabayashi, “Wheels of fortune: Subway expansion and property values in Beijing,” *Journal of Regional Science*, 2016, *56* (5), 792–813.

McFadden, Daniel, “Modeling the choice of residential location,” *Transportation Research Record*, 1978, (673).

Parry, Ian WH and Kenneth A Small, “Does Britain or the United States have the right gasoline tax?," *American Economic Review*, 2005, *95* (4), 1276–1289.

— **and** — , "Should urban transit subsidies be reduced?," *American Economic Review*, 2009, *99* (3), 700–724.

Phaneuf, Daniel J, V Kerry Smith, Raymond B Palmquist, and Jaren C Pope, "Integrating property value and local recreation models to value ecosystem services in urban watersheds," *Land Economics*, 2008, *84* (3), 361–381.

Rhode, Paul W and Koleman S Strumpf, "Assessing the importance of Tiebout sorting: Local heterogeneity from 1850 to 1990," *American Economic Review*, 2003, *93* (5), 1648–1677.

Roback, Jennifer, "Wages, rents, and the quality of life," *Journal of political Economy*, 1982, *90* (6), 1257–1278.

Rosen, Sherwin, "Wage-based indexes of urban quality of life," *Current issues in urban economics*, 1979, pp. 74–104.

Sieg, Holger, V Kerry Smith, H Spencer Banzhaf, and Randy Walsh, "Estimating the general equilibrium benefits of large changes in spatially delineated public goods," *International Economic Review*, 2004, *45* (4), 1047–1077.

Small, Kenneth A., "Valuation of travel time," *Economics of Transportation*, December 2012, *1* (1-2), 2–14.

Timmins, Christopher and Jennifer Murdock, "A revealed preference approach to the measurement of congestion in travel cost models," *Journal of Environmental Economics and management*, 2007, *53* (2), 230–249.

Tra, Constant I., "A discrete choice equilibrium approach to valuing large environmental changes," *Journal of Public Economics*, February 2010, *94* (1-2), 183–196.

Viard, V Brian and Shihe Fu, "The effect of Beijing's driving restrictions on pollution and economic activity," *Journal of Public Economics*, 2015, *125*, 98–115.

Walsh, Randy et al., "Endogenous open space amenities in a locational equilibrium," *Journal of urban Economics*, 2007, *61* (2), 319–344.

Wang, Lanlan, Jintao Xu, and Ping Qin, "Will a driving restriction policy reduce car trips? - The case study of Beijing, China," *Transportation Research Part A: Policy and Practice*, 2014, *67*, 279–290.

Yang, Jun, Avralt-Od Purevjav, and Shanjun Li, "The Marginal Cost of Traffic Congestion and Road Pricing: Evidence from a Natural Experiment in Beijing," *Manuscript*, 2018.

— , **Shuai Chen, Ping Qin, Fangwen Lu, and Antung A Liu**, "The effect of subway expansions on vehicle congestion: Evidence from Beijing," *Journal of Environmental Economics and Management*, 2018, *88*, 114–133.

Zhang, Wei, C-Y Cynthia Lin Lawell, and Victoria I Umanskaya, "The effects of license plate-based driving restrictions on air quality: Theory and empirical evidence," *Journal of Environmental Economics and Management*, 2017, *82*, 181–220.

Zheng, Siqi and Matthew E Kahn, "China's bullet trains facilitate market integration and mitigate the cost of megacity growth," *Proceedings of the National Academy of Sciences*, 2013, p. 201209247.

Figures & Tables

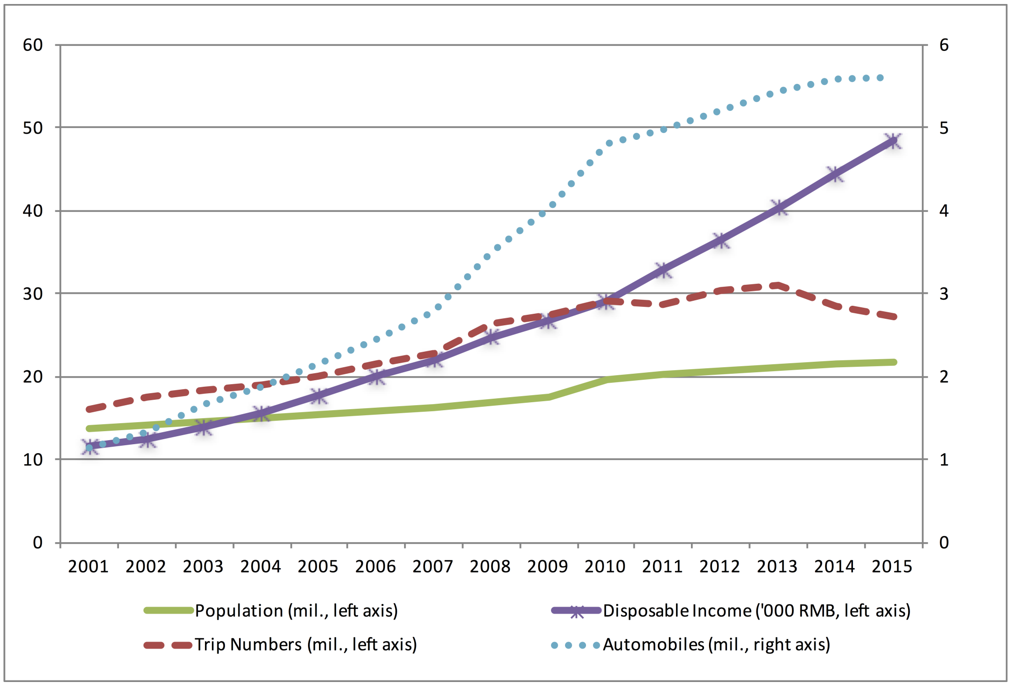


Figure 1: Car Ownership in Beijing

Note: The figure plots trends for Population, Disposable Income, Number of Vehicle Trips and Registered Automobiles in Beijing over 2001-2015. Data come from the China Statistical Yearbook.

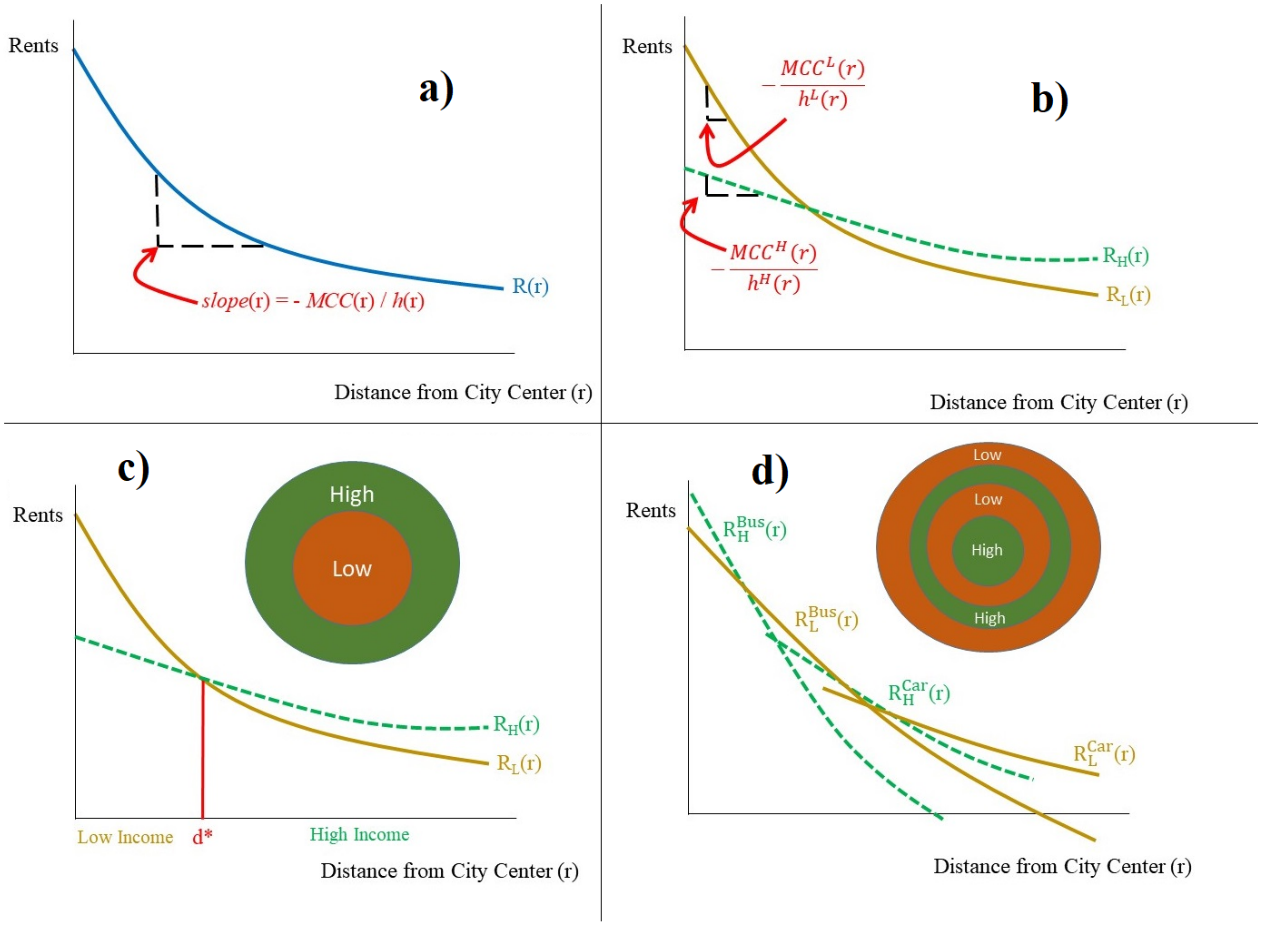
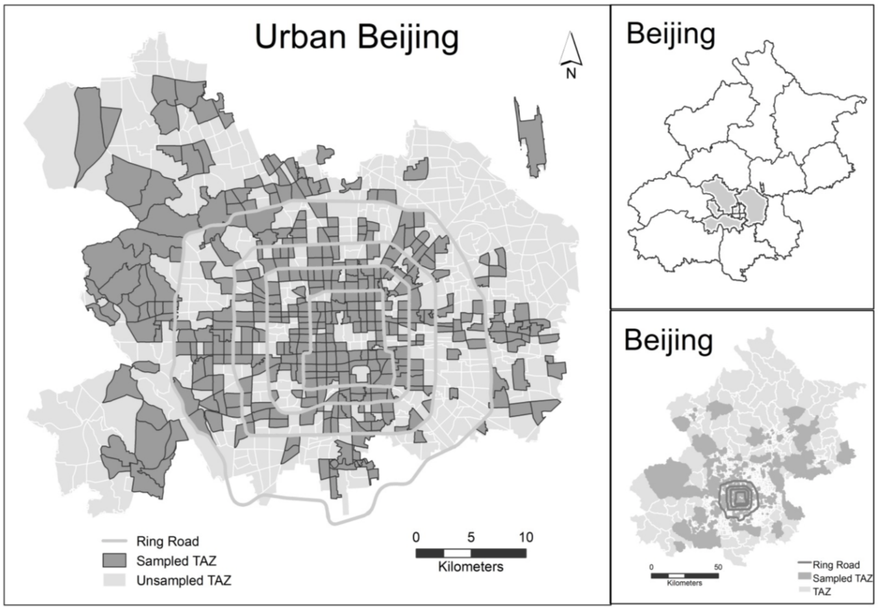


Figure 2: Monocentric City Bid-Rent Diagrams

Note: The figure above displays four possible sets of equilibrium bid-rent functions from the monocentric city model detailed in Section 3. Panel a) shows the equilibrium for homogeneous households choosing consumption between housing and a numeraire good with a single commuting technology. Panel b) allows households to vary by in preferences by income. Panel c) shows the same equilibrium as panel b), but illustrates distribution of households across space. Panel d) shows an alternate set of equilibrium bid-rent functions for a scenario where bus commuters live closest to the CBD, and by mode high income households live closest to the CBD.

(a) Traffic Analysis Zones in Beijing



(b) Distrct-Ring Road Intersections

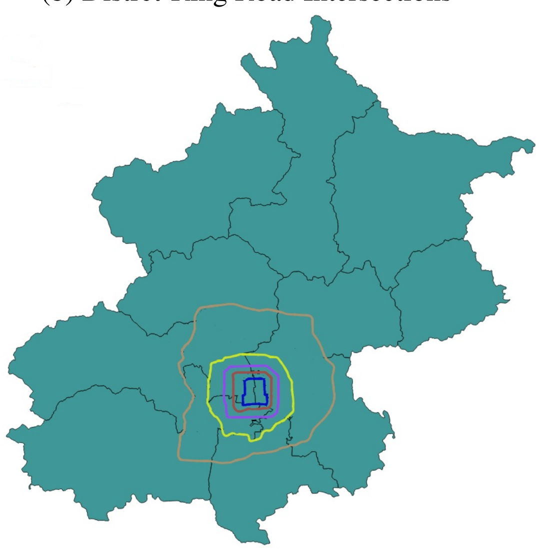


Figure 3: Transportation Regions Considered in Study

Note: Panel (a) of the figure displays the sampling of the 2010 Beijing Household Travel Survey. Each of the small polygons corresponds to a Traffic Analysis Zone, where the sampled TAZs are located predominantly within the central, more populated parts of Beijing–specifically within the 6th ring road. Panel (b) shows the regions used to calculate travel times and distances for the housing data, which are polygons formed by the intersection of the ring roads with district boundaries.

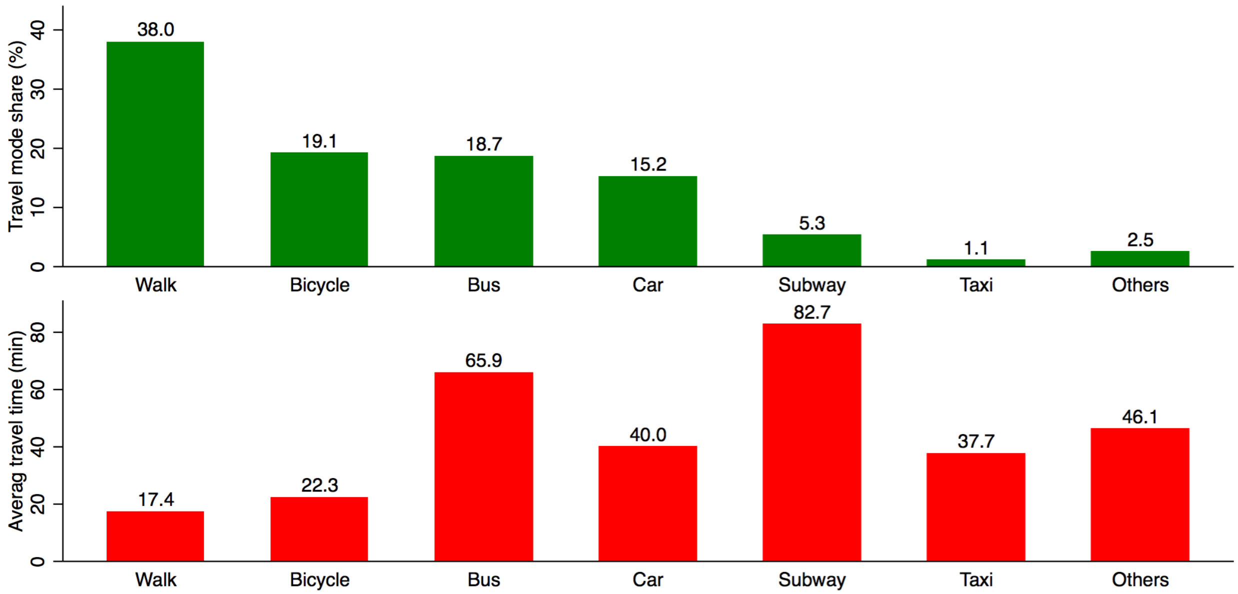


Figure 4: Trip Share, Time and Cost by Mode

Note: This figure shows summary statistics for data from the 2010 Beijing Household Travel Survey. The first bar chart displays the share of trips taken by each mode type. The second chart shows the average travel time for each travel mode.

(a) No Policy & Subway Expansion (b) Driving Restriction & Congestion Charge

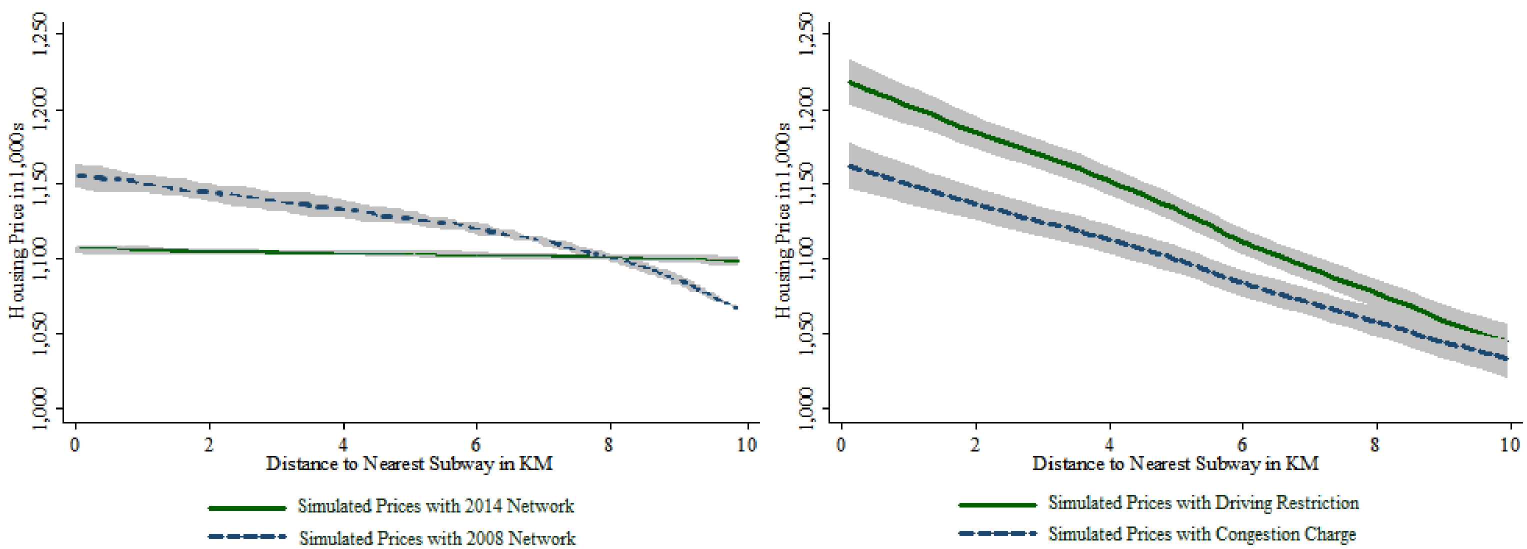


Figure 5: Simulated Price Gradients: Distance to Subway

Note: This figure shows simulated price gradients based on equilibrium prices for which predicted demand from the model equate to the supply of houses. The horizontal axis reports the distance to the nearest subway station from each house in kilometers. The dashed line is based on the 2008 subway network and the solid line is the 2014 subway network. Panel (a) reports the effect with only a subway expansion, where we have simulated behavior as if there had been no driving restriction. Panel (b) reports simulated prices with the driving restriction and congestion charge in place.

Table 1: Summary Statistics

Panel A: Travel Survey				
Variable	Mean	SD	Min	Max
Household size	2.47	0.98	1	5
Income (RMB ’000)	64.49	30.21	50	300
# of workers	1.18	0.92	0	4
House size (m^2)	75.85	49.61	5	3,800
House owner (=1)	0.69	0.46	0	1
Having a car (=1)	0.29	0.45	0	1
# of cars	0.31	0.51	0	3
# of bikes	0.96	0.93	0	5
# of ebikes	0.15	0.40	0	4
# of motorcycles	0.03	0.18	0	3

Panel B: Mortgage Data				
Year	2010	2	2008	2014
Household Income (1,000s 2010 RMB)	153.7	81.0	15.1	717.1
Borrower Age	33.0	5.6	23	55
Real House Sale Price (1,000s 2010 RMB)	957.7	0.0	193.9	3,303.2
Unit Size (square meters)	85.8	30.5	36.4	199.6
Distance to Work (km)	10.5	7.4	0.1	53.3
Distance to Subway from Home (km)	5.24	8.78	0.26	51.99

Note: Panel A of the table reports summary statistics for 12,105 home-to-work or work-to-home trips in the travel survey data. Panel B reports summary statistics for the 13,865 homes that are used to construct the mortgage data sample.

Table 2: Estimates of travel mode choice

	(1)	(2)	(3)	(4)
Panel A: Mode Choice Estimation (MLE)				
Time (hours)	-0.728***	-0.135***	-0.133***	-0.139***
Cost/Income	0.227***	-0.196***	-0.271***	-0.243***
Case variables				
ASC	Y	Y	Y	Y
Distance	N	Y	Y	Y
Age	N	N	Y	Y
Male	N	N	Y	Y
Schooling	N	N	Y	Y
HH size	N	N	N	Y
# of cars	N	N	N	Y
# of workers	N	N	N	Y
N of Trips	12105	12105	12105	12105
Pseudo R^2	0.059	0.141	0.180	0.199
$\log \ell$	-15352.1	-14014.5	-13375.2	-13075.5

Panel B: Implied VOT

Income (RMB/year)	Wage (RMB/h)	VOT (RMB/h)	Wage ($/h)	VOT ($/h)
25000	12.50	7.12	1.98	1.13
75000	37.50	21.38	5.93	3.38
125000	62.50	35.62	9.89	5.64
175000	87.50	49.88	13.84	7.89
225000	112.50	64.12	17.80	10.15
275000	137.50	78.38	21.76	12.40
325000	162.50	92.62	25.71	14.66
Average	37.05	21.12	5.86	3.34

Note: Table reports estimates from maximum likelihood estimation of multinomial logit model of mode choice between driving, walking, biking, subway and bus. Panel A reports coefficients and specifications, where alternative-specific constants are included but not reported. Panel B reports the implied distribution of wages, value of time (VOT) in RMB and USD. Sample is restricted to work-home or home-work trips, at least one car and one bike, age between 16 and 60, within the 6th Ring Road. The value of time (VOT) is calculated as: $VOT = \frac{\frac{\partial v_i}{\partial time_i}}{\frac{\partial v_i}{\partial cost_i}} = \frac{\hat{\gamma}_{time}}{\hat{\gamma}_{cost}} \cdot Income_i = 0.57 \cdot Income_i$. The omitted fixed effect in the model estimated is for walking.

Table 3: Estimates from Location Choice Model

	(1)		(2)	
Panel A: First Stage Estimates (MLE) - 20 Sampled Alternatives				
	Specification I		Specification II	
Variable	**coef.**	**std. error**	**coef.**	**std. error**
$\frac{\text{log(housing price)}}{\text{log(HH income)}}$	-0.974	0.0093	-1.17	0.0085
age buyer*unit size	0.0009	0.00007	0.0009	0.00007
(age buyer)^2*unit size	-7.2$*10^{-6}$	1.5$*10^{-7}$	-6.5$*10^{-6}$	1.5$*10^{-7}$
mode choice log sum	0.0037	0.0007		
Households	13,865		13,865	
Housing Types	548		548	
Log-Likelihood	-495,483		-496,885	
LR p-val (H0: $\delta = 0$)	0.00		0.00	
McFadden pseudo-R^2	0.54		0.51	

	(1)		(2)		(3)	
Panel B: Second Stage Estimates: Dependent variable is $\hat{\delta}_{jt}$						
	OLS		**OLS**		**IV**	
variable	**coef.**	**S.E.**	**coef.**	**S.E.**	**coef.**	**S.E.**
log(total price)	-0.470	0.24	-0.271	0.233	-1.736	0.773
Dist. to center	-0.0125	0.00925	-0.0225	0.00927	-0.0522	0.0268
unit size in m^2	0.149	0.0158	0.128	0.015	0.138	0.0192
(unit size)^2	-0.00070	8.74$*10^{-05}$	-0.00061	8.23$*10^{-05}$	-0.00060	8.52$*10^{-05}$
constant	-0.399	3.255	-1.954	3.176	17.34	13.37
Observations	548		548		548	
R^2	0.22		0.36		0.31	
Year FE	X		X		X	
District x Ring Road FE			X		X	
1st Stage F-Stat					11.9	

Note: Table reports estimates from a two-stage estimate of demand for housing. The first stage estimates are presented in Panel A, where "mode choice logsum" is EV_j constructed using data for households and estimates from the mode choice model from Table 2. First stage housing type fixed effects are estimated through the contraction mapping in this first stage and are used as the dependent variable in the second stage reported in Panel B. Panel B estimates are based on housing type attributes and are estimated by OLS and IV, where the instruments are the mean of housing attributes other than price within 1-5km rings from the housing types.

Table 4: Simulation Results: Commuting Mode Only

	(1) Baseline No Policy *(in levels)*		(2) Driving Restriction *(change rel. to I)*		(3) Congestion Charge *(change rel. to I)*		(4) Subway Expansion *(change rel. to I)*	
	Household Income Relative to Median							
	Below	**Above**	**Below**	**Above**	**Below**	**Above**	**Below**	**Above**
Mode Use Share in Percentage Points								
Drive	0.07	0.38	-0.01	-0.08	-0.02	-0.01	-0.01	-0.02
Subway	0.03	0.12	0.00	0.03	0.00	0.01	0.02	0.07
Bus	0.32	0.15	0.01	0.04	0.01	0.00	0.00	-0.02
Bike	0.17	0.10	0.00	0.00	0.01	0.00	-0.01	-0.01
Walk	0.41	0.25	0.00	0.01	0.00	0.00	0.00	-0.02
Speed (kph)	57.8	57.6	2.3	2.4	1.6	1.8	0.9	0.8

Note: Table reports results from three counterfactual policy simulations based on 2014 observations relative to simulated baseline no-policy equilibrium with 2008 subway network (column I): driving restriction, 20 RMB congestion charge and expanding the subway from 2008 to 2014 network. “Change in Mode Use Share” reports how the share of commuters in each income quartile changed their commuting choice (0.03 means that the share using that mode increased by 3 basis points)

Table 5: Simulation Results: Commuting & Location Choice

	(1) Baseline No Policy *(in levels)*		(2) Driving Restriction *(change rel. to I)*		(3) Congestion Charge *(change rel. to I)*		(4) Subway Expansion *(change rel. to I)*	
	Household Income Relative to Median							
	Below	**Above**	**Below**	**Above**	**Below**	**Above**	**Below**	**Above**
Mode Use Share in Percentage Points								
Drive	0.08	0.37	-0.04	-0.15	-0.04	-0.07	-0.01	-0.07
Subway	0.03	0.11	0.02	0.07	0.01	0.05	0.02	0.12
Bus	0.32	0.15	0.02	0.03	0.01	0.02	-0.01	-0.02
Bike	0.17	0.11	0.01	0.01	0.02	0.00	0.00	-0.01
Walk	0.40	0.26	0.01	0.02	0.00	0.00	0.00	-0.02
Dist. to Subway in KM	1.89	4.21	0.08	-0.03	-0.03	0.10	0.08	-1.11
Dist. to Work in KM	10.1	9.40	1.94	-1.01	-2.9	2.5	1.09	-2.0
Speed in KPH	57.8	57.6	3.5	3.5	2.8	2.9	1.8	1.7

Note: Table reports results from three counterfactual policy simulations based on 2014 observations relative to simulated baseline no-policy equilibrium with 2008 subway network (column I): driving restriction, 20 RMB congestion charge and expanding the subway from 2008 to 2014 network. "Change in Mode Use Share" reports how the share of commuters in each income quartile changed their commuting choice (0.03 means that the share using that mode increased by 3 basis points).

Table 6: Simulation Results: Welfare Effects

Δ *Consumer Surplus in 1,000s 2010 RMB*	(1) **Driving Restriction**		(2) **Congestion Charge**		(3) **Subway Expansion**	
	Household Income Relative to Median					
	Below	**Above**	**Below**	**Above**	**Below**	**Above**
Travel Mode Only	-2.81	-14.12	-3.33	-12.95	1.08	3.21
Travel Mode & Location	-2.68	-11.54	-3.56	-10.81	1.39	5.41

Note: The Table reports welfare estimates from 6 model simulations measuring differences in consumer surplus for the simulated equilibrium outcome relative to the outcome with no policy. "Travel Mode Only" only allows households to change their commuting mode in response to the simulated policy change, while "Travel Mode & Location" allows them to change their mode and housing location.