Efficiency and Equity Impacts of Urban Transportation Policies with Equilibrium Sorting

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Abstract

We estimate an equilibrium model of residential sorting with endogenous traffic congestion to evaluate the efficiency and equity impacts of urban transportation policies. Leveraging fine-scale data on household travel and housing transactions with home and job locations in Beijing, we jointly estimate residential location and travel mode choices and recover households' preference for the ease of work commute and other attributes of residential locations. Counterfactual simulations show that while different policies can attain the same level of congestion reduction, their impacts on residential sorting and social welfare are drastically different. First, a driving restriction intensifies income-stratified urban structure where high-income households live closer to subway and jobs. Distance-based congestion pricing reduces the spatial separation between residence and workplace across income levels, while subway expansion does the opposite. Second, residential sorting strengthens the effectiveness of congestion pricing in improving traffic conditions but undermines that of the driving restriction and subway expansion. Third, the driving restriction is welfare reducing as it leads to large distortions on travel choices. Congestion pricing improves welfare but is regressive, highlighting the need to recycle revenue to address the associated equity concern. Finally, congestion pricing and subway expansion deliver the largest congestion relief and efficiency gain when combined. This policy mix is self-financing in that revenue from congestion pricing could fully cover the cost of subway expansion.

Keywords: equilibrium sorting, housing markets, transportation, urban structure

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1 Introduction

A key insight from urban economics is that changes in transportation systems have differential implications across income groups on the quality of urban living as mediated through the housing market (LeRoy and Sonstelie, 1983). Recent literature has empirically documented that transportation plays a crucial role in urban spatial structure and the organization of economic activity (Allen and Arkolakis, 2019; Tsivanidis, 2019; Heblich et al., 2020; Gorback, 2020). In most fast-growing developing countries, rapid urbanization and motorization together with poor infrastructure have created unprecedented traffic congestion with severe consequences for economic outcomes (Akbar et al., 2018; Harari, 2020).[1] To address this challenge, local governments around the world have implemented a suite of policies, including driving restrictions, gasoline taxes, public transit investment, and congestion pricing. In the short term, the effectiveness of these policies crucially hinges on the substitutability among travel modes and the sensitivity of travel demand to changes in the cost of commuting and availability of alternative modes. In the medium to long run, these policies are likely to have broader impacts on residential location choices and urban spatial structure, which, in turn, could mediate the effectiveness of these policies and have important distributional consequences. This paper aims to understand the efficiency and equity impacts of urban transportation policies while accounting for the interaction between these policies and residential location decisions. To do so, we jointly model residential locations and travel mode choices in an equilibrium sorting framework with endogenous congestion.

The empirical context of our study is Beijing, which has a population of 21.5 million and has been routinely ranked as one of the most congested cities in the world. Severe congestion has major implications for air pollution and misallocation of time and negatively affects the quality of urban life (Kahneman and Krueger, 2006; Anderson et al., 2016). Beijing's municipal government has adopted several policy interventions to aggressively combat traffic congestion and air pollution, including a driving restriction policy from 2008 that restricts vehicles from driving one day per week during weekdays based on the last digit of the license plate. It also invested a staggering \$100 billion in transportation infrastructure between 2007 and 2018 and added 16 new subway lines with a total length of 523 kilometers and more than 200 additional bus lines, a major upgrade of Beijing's public transit network. Despite these efforts, Beijing has only seen a small increase in the use of public transit and a modest reduction of peak-hour traffic congestion since 2015. The city's experience, common among urban centers around the world, echos long-standing concerns from economists that without appropriate road pricing, effective congestion management is unlikely (Vickrey, 1959, 1963).

Beijing's policies to combat congestion – driving restrictions and subway expansion – together with its proposed policy on congestion pricing embody three general approaches to the regulation of unpriced externalities: command-and-control, supply-side, and market-based approaches, respectively. To understand the

[1] Based on real-time GPS traffic data in 403 cities from 56 countries in 2018, the TomTom Traffic Index shows that the 10 most congested cities were all from developing and emerging economies. The top five cities were Mumbai, Bogota, Lima, New Delhi, and Moscow. Drivers in Mumbai spent 65% more commuting time on average than they would have under the free flow condition, while drivers in Beijing (the number 30 on the list) spent 40% extra time on the road. Four cities in China were among the top 30 on the list. Los Angeles, the most congested city in the US, was ranked 24^{th} with a congestion index of 41%. The full ranking based on the TomTom Traffic index 2018 is available at `https://www.tomtom.com/en_gb/traffic-index/ranking.`

primary channels by which these policies affect travel mode and housing choice, we first develop a stylized theoretical model based on LeRoy and Sonstelie (1983) and Brueckner (2007) while accounting for endogenous congestion and heterogeneity in income and commuting technologies. The model shows the differential impacts of urban transportation policies on the spatial pattern of residential locations and potential distributional consequences across income groups. The discussion illustrates the countervailing forces at play between mode choice and housing location. The model also demonstrates how the general equilibrium effects of transportation policies on the housing market can have efficiency and distributional consequences. Lastly, the model highlights the ambiguity in qualitative comparative statics even for simple models with two income types and two commuting technologies, demonstrating the need for subsequent empirical analysis to understand how these factors play out in an actual urban setting.

Our empirical analysis is made possible by two comprehensive data sets. The first is the Beijing Household Travel Survey (BHTS) from 2010 and 2014, a large representative survey that records households' home and work locations, trips made in a 24-hour window and other demographic and transportation-related information. We complement this data by constructing the counterfactual commuting distance from home to work using historical Geographical Information System (GIS) maps and the Application Programming Interface (API) from online mapping services. This exercise allows us to calculate commuting routes, travel times, distances and pecuniary travel costs for each trip-mode combination (walking, biking, taking a bus, subway, car, or taxi). The second data set contains mortgage transactions from a government-run mortgage program and provides a large representative sample of Beijing home buyers. Critical to our analysis, the housing data contain not only property location information but also job locations of both the primary and secondary borrowers. Using this information, we construct over 12 million hypothetical trip-mode combinations of the home-work commute for both the primary and second borrowers using the same GIS and API procedure as was done for the travel survey data. Based on the time and pecuniary costs of these hypothetical commutes we are able to construct a measure on the work-commute attractiveness for each home buyer for each property in the buyer's choice set, which we call an "ease-of-commuting" attribute of housing choice. For a given house and a potential buyer, the ease-of-commute corresponds to the expected maximum utility of commuting from the house to the buyer's job location.

We leverage the commuting and housing data to estimate an equilibrium model of residential sorting with endogenous congestion while incorporating preference heterogeneity and allowing for general equilibrium feedback effects between housing and commuting decisions. In the model, households choose housing units based on their preference for housing attributes, neighborhood amenities (e.g., schools and parks), and ease-of-commuting from home to work. The proximity to public transit and the level of traffic congestion in different parts of the city play a key role in determining the extent of ease-of-commuting. We allow traffic congestion level in Beijing to be an equilibrium outcome that arises from location choices and travel decisions of all households. Once estimated, the model allows us to conduct counterfactual simulations to predict new equilibrium outcomes for both marginal and non-marginal policy changes in terms of housing prices, household locations, travel mode choices, and the congestion level.

We use a two-step strategy to estimate the equilibrium sorting model. The first step is to recover consumer preferences for travel time and cost (therefore the value of time) using the household travel survey data. We then utilize the estimated parameters from this step to construct the aforementioned ease-of-commute index for buyers appearing in our mortgage dataset. The calculated index accounts for preference heterogeneity of home buyers related to income as well as changes in the transportation system between the travel survey and home purchase dates. The second step recovers preference for housing attributes in a housing demand model. The ease-of-commute index is included as an observed (buyer-specific) property attribute in this step. The key identification challenge in the housing demand model is the potential correlation between unobserved housing attributes and the price as well as the ease-of-commute index. Both of these last two variables are equilibrium outcomes determined by observed and unobserved housing attributes. To address this challenge, we allow preferences to vary conditional on observed and unobserved buyer demographics and include property fixed effects through maximum-likelihood estimation with a nested contraction mapping (Train and Winston, 2007). In the spirit of Berry et al. (1995) and Bayer et al. (2007), we construct instrumental variables for housing price based on three sets of variables: average housing and neighborhood attributes of properties at a reasonable distance from a given property, time-varying odds of winning a lottery on licenses to purchase a vehicle, and the number of homes sold in a three-month window around the sale date.

Utilizing these estimates, we then simulate equilibrium housing and transportation outcomes based on the three policies of interest in our study: the license plate-based driving restriction, subway expansion from the 2008 to 2014 network, and congestion pricing. Since the first two policies have been enacted, we begin with a no-policy counterfactual and then compare this baseline to each policy as well as their combinations. We are also able to compare partial equilibrium outcomes that do not allow residential sorting to a general equilibrium that allows households to relocate in response to transportation policy. Our simulations also account for potential adjustments in housing supply in response to changes in equilibrium housing prices and congestion. Our policy simulations yield four key findings.

First, although different transportation policies can attain the same level of congestion reduction, they exhibit different and even opposite impacts on the housing market and the spatial pattern of residential locations. Both the driving restriction and congestion pricing increase the price premium of properties near city center and subway stations, as high-income households outbid low-income households for these locations. As a result, the driving restriction reduces the distance to work for high-income households but increases that for low-income households. In contrast, distance-based congestion pricing reduces distance to workplace for both income groups, while subway expansion leads to the opposite effect.

Second, residential sorting can either strengthen or undermine the congestion-reduction potential of transportation policies as well as the welfare impacts. Sorting strengthens the impact of congestion pricing in both congestion reduction and welfare gain as households are incentivized to live closer to job locations and take public transportation, walk or bike. On the other hand, sorting in response to subway expansion would lead to a larger separation between housing and job locations, damping the congestion reduction effect and welfare gain from infrastructure investment. The implication of sorting on the effectiveness of driving restrictions is more nuanced and depends on the extent of reduction in average commuting distance and the increased propensity of driving for more distant trips. Our analysis finds that sorting only slightly weakens the effectiveness of the driving restriction.

Third, transportation policies generate equity impacts, and could exacerbate or alleviate economic inequality (Waxman, 2017; Akbar, 2020). Congestion pricing provides a larger welfare gain for low-income households than high-income households if its revenue can be uniformly recycled. Without recycling, however, pricing is regressive and leads to a larger overall welfare loss for low-income households. This distributional concern is an important impediment to congestion pricing adoption in practice. The driving restriction policy is progressive as it leads to less distortion on travel decisions for low-income households, potentially explaining the wider adoption of this policy than congestion pricing around the world.

Finally, the actual and hypothetical transportation policies have different implications on aggregate welfare. Beijing's rapid subway expansion from 2008 to 2014 led to an increase in consumer surplus and aggregate welfare despite modest congestion reduction. In contrast, driving restriction is welfare reducing despite a larger congestion reduction. Congestion pricing and subway expansion in tandem deliver the largest improvement in traffic speed and welfare gain. In addition, the revenue from congestion pricing could fully finance the capital and operating costs of subway expansion, eliminating the need to fund the expansion from other distortionary taxes. These results showcase the sorting model's strength in capturing various margins of adjustment and its ability to compare different policy scenarios in a unified framework that accounts for general equilibrium welfare effects with preference heterogeneity.

Our study makes three main contributions to the literature. First, while quantitative spatial economics has made considerable advances to explore the role of transportation in urban systems (see Redding and Rossi-Hansberg (2017) for a review), there has been little attempt in the empirical urban literature to explore the role of preference heterogeneity and congestion externalities in mediating the welfare effects of different transportation policies. While he urban literature has long pointed to "wasteful commuting" that results in equilibrium housing and transportation choices deviating from social optimum (Hamilton and Röell, 1982; Cropper and Gordon, 1991), accounting for preference heterogeneity could be crucial for understanding the equilibrium and distributional impacts of urban policies. With growing concerns about the role of location in economic opportunity (Chetty et al., 2014), the rich preference heterogeneity incorporated in our framework allows us to identify winners and losers from urban transportation policies, in the spirit of the theoretical and reduced form work by LeRoy and Sonstelie (1983), Glaeser et al. (2008) and Brueckner et al. (1999). As some more recent quantitative spatial models (Allen and Arkolakis, 2019; Fajgelbaum and Gaubert, 2020), we explicitly model endogenous congestion to capture its increasing marginal external cost, as highlighted by Anderson (2014). Critically, our dual-market approach provides a micro-foundation for the hedonic models that study the capitalization of transportation investment in the housing market (Baum-Snow and Kahn, 2000; Gibbons and Machin, 2005; Zheng and Kahn, 2013) and demonstrates considerable distributional impacts from household sorting.

Second, our analysis contributes to a large equilibrium residential sorting literature by showing the importance of endogenous work commuting decisions in understanding residential location choices. Sorting models have been used to study consumer preferences for local public goods and urban amenities (e.g., air quality, school quality, and open space) and evaluate policies to address economic, social and environmental challenges (Epple and Sieg, 1999; Kuminoff et al., 2013).[2] Most existing papers use the distance to work as an exogeneous measure of the ease-of-commute despite the fact that it reflects endogenous travel mode choices and traffic congestion. Our approach is perhaps closest to Kuminoff (2012) which allows for households to make decisions in both the job and housing market and take into account the work commute. However, it treats congestion as exogenous and the commuting time is affected solely by the distance. Our paper is the first to our knowledge in the empirical sorting literature that explicitly models congestion as an equilibrium outcome that is simultaneously determined by household location and travel mode choices.

Third, our paper relates to the literature on transportation policies that address negative externalities associated with vehicle usage (Parry et al., 2007).[3] Studies in this literature commonly focus on short-run or partial equilibrium effects of transportation policies on travel choices, traffic congestion, and air pollution. By characterizing underlying travel and housing choices, our equilibrium sorting framework provides a microfoundation for the reduced-form impact evaluation studies. More importantly, the unified framework offers a common yardstick to evaluate actual and counterfactual policies in a range of outcomes including congestion reduction, urban spatial structure, social welfare, and distributional consequences. A few studies examine the general equilibrium feedback effects through housing location such as Anas and Kim (1996) and Langer and Winston (2008), which evaluate transportation policies taking into account their impacts on land use. Compared with the calibrated computable general equilibrium analysis, our approach is internally consistent in that the estimation of structural parameters and the policy simulations are based on the same equilibrium sorting model.

Section 2 uses a stylized model to explain the key forces underlying the interaction between housing and transportation. Section 3 describes the data and provides reduced-form evidence on the effect of Beijing's driving restriction on the housing market to motivate and ground subsequent simulation results. Section 4 lays out the equilibrium sorting model and the estimation strategy. Estimation results are provided in Section 5. Section 6 conducts simulations to examine the impacts of transportation policies and compare their welfare consequences. Section 7 concludes.

[2] See for example Bayer et al. (2007); Ferreyra (2007); Epple and Ferreyra (2008); Epple et al. (2012) on school quality, Sieg et al. (2004); Bayer et al. (2009); Kuminoff (2009); Tra (2010); Bayer et al. (2016) on air quality, Timmins and Murdock (2007); Walsh et al. (2007); Klaiber and Phaneuf (2010) on open space and recreation, Bajari and Kahn (2005); Bayer et al. (2007); Bayer and McMillan (2012); Hwang (2019) on racial and ethnic composition, Calder-Wang (2020) on the distributional impacts of the sharing economy in the housing market. Several recent studies seek to incorporate dynamic models of housing demand into sorting, allowing for households to make choices based on expectations about the evolution of location amenities, prices and wages over time on endogenous amenities as a bundle (Domínguez-Iino, 2020; Murphy, 2015; Wang, 2020). We do not incorporate dynamics into our model but consider their influence in our interpretation of the results.

[3] Various policies have been evaluated. See Parry and Small (2005); Bento et al. (2009); Knittel and Sandler (2013); Li et al. (2014) on gasoline taxes, Bento et al. (2005); Parry and Small (2009); Duranton and Turner (2011); Anderson (2014); Basso and Silva (2014); Li et al. (2019); Severen (2019); Gu et al. (2020) on public transit subsidies and expansion, Davis (2008); Viard and Fu (2015); Carrillo et al. (2016); Zhang et al. (2017) on driving restrictions, and Langer and Winston (2008); Anas and Lindsey (2011); Hall (2018); Yang et al. (2019); Kreindler (2018) on congestion pricing.

2 Theoretical Framework

We begin by motivating our setup with two graphical presentations of the welfare effects of two of the transportation policies examined in our empirical analysis: congestion pricing and driving restrictions. There are two dimensions of this effect captured: that in the primary market for commuting reflecting the direct effect of an unpriced externality on the marginal social cost of driving, and a secondary effect on a related market, housing, where changes in commuting costs are capitalized into housing prices and can induce changes in commuting mode choice and housing location.[4]

Figure 1 illustrates the welfare effects of these two policies in the primary "market" for vehicle road traffic. Here, the economic cost induced by congestion can be demonstrated in terms of the level of traffic volume, V as the difference between marginal social cost (MSC) and Average Social Cost (ASC) and the unpriced externality created by the marginal external cost of congestion (MEC). Both congestion pricing and a driving restriction result in a reduction of traffic volumes from the unregulated level, V^0, to the socially optimal level, V^*. However, congestion pricing reduces the trips with the lowest marginal benefit while the driving restriction, due to the fact that its design does result in sorting based on differences in the value of time, could reduce trips with various levels of marginal benefit.[5] If the length of commuting trips are reduced in a random manner, the driving restriction will lead to welfare loss equivalent to the blue triangle in Figure 1. The size of the triangle is positively related to the degree of heterogeneity in the marginal benefit of trips. The figure illustrates that while congestion pricing leads to welfare gain, the welfare impact of a driving restriction is ambiguous.

However, Figure 1 is only a partial equilibrium analysis that does not take into account the potential impact of transportation policies on proximate markets. It also tells us little about differences in these incomes across individuals. To understand these additional effects, consider a monocentric city model where households with different incomes sort into different locations in response to transportation policies based principally on their deterministic preferences for housing, other goods and time.[6] This model includes three key components of recent applied work in urban economics: endogenous congestion, mode choice, and residential sorting. We fully develop this model in Appendix A including presenting key comparative statics building on the approach from Brueckner (2007), but here we summarize some key properties, standard in this class of models, and elaborate on a set of stylized outcomes that illustrate heterogeneous welfare effects via capitalization.

Model Primitives Here are the key model primitives:

- The monocentric city is linear with a fixed population (N) of rich, N_R, and poor, N_P, residents.

[4]Following Roback (1982), there is also a capitalization in the labor market but this lies outside the scope of our study.

[5]In this sense, driving restrictions correspond to classic command-and-control or mandate-based quantity restriction form of environmental policy. On the other hand, congestion pricing corresponds to a traditional market-based approach. We use these designations interchangeably in this paper.

[6]In our empirical analysis, we will relax assumptions of monocentricity and allow for random utility.

- All residents work at the urban center (CBD) at location 0, where wage income for the rich is larger: $y_R > y_P$.[7]

- The rest of urban space is occupied by houses with lot sizes normalized to 1 and where land rents are remitted to absentee landlords.

- Households maximize utility via housing and non-housing consumption subject to a budget constraint that includes commuting costs and varies between rich and poor based on their value of time (higher for the rich).

- Housing consumption (in square meters) is provided by perfectly competitive developers.

- Beyond the residential area is agricultural land, which returns rental value p_a.

Commuting Technology Several key features characterize the nature of commuting technology:

- Two commuting modes exist in the city: personal vehicles with higher fixed costs and lower variable costs relative to the alternative commuting mode, subway.

- Variable costs, denoted $w_{d,m}(x)$ for mode $m = car, subway$ and group $d = R, P$, include time and pecuniary costs.

- Travel time is monetized by the value of time (VOT): $v_R > v_P$.[8]

- We begin by assuming that the subway network covers the entire urban area and then relax this assumption when considering the role of public transportation infrastructure.

- Car commuting suffers from endogenous congestion determined by the commuting choices of all other households in the city. We ignore the role of congestion in public transportation and focus solely on its effect on car travel.

- The model is a closed-city model with intracity, but not intercity migration.[9]

A feature of the model that usefully simplifies the analysis is that changes in commuting cost will not affect the overall size of the city as reflected by the location of the urban boundary, $\bar{x}$, since the population is fixed and land use per household is also fixed.

[7] Given the linear structure of the city, we assume roads take up no space and all land goes towards housing.

[8] We also assume that fixed commuting costs are larger but variable costs (without congestion) are lower for car relative to subway.

[9] Public transit congestion and closed-city assumptions could be relaxed without affecting the key predictions of the model. Brueckner (1987) provides an analysis of a monocentric city model with a perfectly competitive supply side for both cases of a closed and open city.

Equilibrium Properties Given a mass of rich and poor households residing and working in the city, a spatial equilibrium is determined by a bid rent function $p^*(x)$ that is the envelope of individual willingness-to-pay for housing based on mode and housing type at each point, x, in the city,[10] keeping the utility for each income type fixed at $\bar{u}_d$, $d = R, P$:

$$p^*(x) = \max_{d,m} \left\{ p\left(y_d - \theta_m - w_{d,m}(x), \bar{u}_d\right) \right\} \qquad d = R, P; m = car, subway. \tag{1}$$

For subway commuters, who are assumed to experience no congestion, the slope of the bid rent function does not change. In residential regions with car commuting, moving from right to left across the region means adding additional car commuters, further increasing per kilometer commuting time costs and steepening the bid rent function.

Model Calibration and Policy Analysis In the Appendix, we explain and show the result of calibration yielding the urban configuration presented in Figure 2: rich subway commuters live closest to the CBD, then poor subway commuters, then rich car commuters, then poor subway commuters. This outcome is not unique and is purely illustrative to yield a pattern of sorting that roughly approximates the qualitative pattern for Beijing described in section 3.[11]

In Figure 2, we show the effect of two transportation policies, congestion pricing and a driving restriction, on the equilibrium bid-rent envelope corresponding to (1). Colored lines in Figure 2 reflect the gradient of housing prices in equilibrium after the indicated transportation policy, where the colors correspond to the bid-rent for the group of commuters indicated below the horizontal axis. Gray lines in both panels reflect the same no-policy baseline price gradient.

The additional welfare effects of transportation policies in the housing market is reflected by the areas between these envelopes. A key principle in urban economics underlying the Rosen (1974) and Roback (1982) approach as well as the Henry George Theorem is that investments in public goods or reductions in negative externalities should be capitalized into housing values and so comparing differences in the sum of housing values can be used to approximate welfare changes under housing and land markets characterized by perfect competition.

Key Model Takeaways In Figure 2, we can see two principal effects of both congestion pricing and driving restrictions on rents and therefore the capitalization of transportation policies: one, the value of proximity to the CBD (i.e., workplace) rises for those nearby (specifically subway commuters), while for those farthest away, it falls. Capitalization gains are larger than losses for congestion pricing (where revenues are recycled lump-sum) because wealthy drivers gain from time savings net of tolls, while the poor who move to the

[10] The full set of market clearing conditions are presented in the Appendix.

[11] In reality, Beijing does not have a single CBD and there are varying patterns of proximity of relatively wealthy to relatively less wealthy across Beijing.

subway commuting area benefit from revenue recycling and shorter commutes net of higher housing costs.[12] Two, rent losses for longer commutes are larger under the driving restriction. This is because those who would ordinarily drive are forced to take the subway for very long commutes on restricted days of the week.

In summary, while the primary effect of transportation policies on commuting costs in the market for driving is straightforward, the secondary effect on housing via price capitalization can be large and depends on relative differences in the marginal cost of commuting, income heterogeneity and preferences for housing and time. While illustrative, this simple model ignores a host of important features important for understanding the economic effects of transportation policies in Beijing such as polycentricity of the city, travel modes beyond driving and subway, and variation in the availability of housing across the city. For these reasons, we now turn to our equilibrium sorting model to empirically evaluate these policies.

3 Data Description and Reduced-form Evidence

3.1 Data Description

To compare the impacts of different transportation policies across commuting and housing location decisions, we construct the most comprehensive data on work-commute travels and housing transactions ever used in the context of equilibrium sorting models. We rely on two main data sets for our analysis: Beijing Household Travel Survey in 2010 and 2014, and housing mortgage data over 2006-2014 with detailed information on household demographics as well as the work address of the buyers.

3.1.1 Beijing Household Travel Survey

We utilize two rounds of the Beijing Household Travel Survey (BHTS) collected in September and October of 2010 and 2014 by the Beijing Transportation Research Center (BTRC), an agency of the Beijing municipal government. Beijing's municipal government uses these surveys to inform transportation policies and urban planing. BHTS is made to be representative using a multistage cluster sampling of households in Beijing. In the first stage, BTRC randomly selects a subset of Traffic Analysis Zones (TAZs) from the entire city. TAZs are one to two square kilometers on average and their size is inversely proportional to the density of trip origins and destinations: smaller TAZs are closer to the center of Beijing. For the first stage of sampling, BTRC selected 642 out of 1,191 TAZs in 2010 and 667 out of 2050 TAZs in 2014, respectively. In the second stage, about 75 and 60 households were randomly selected for in-person interviews for each TAZ. The sample locations are shown in Appendix Figure A6. The BHTS survey includes individual and household demographic and occupational information (e.g., household size, vehicle ownership, home ownership, age, gender, occupation), availability of transportation options (vehicles, bikes, etc.), and a travel diary for the preceding 24 hours. The diary includes information on all trips taken including the origin and destination, the departure and arrival

[12] Panel (a) shows a small, but negligible loss of rents for poor car commuters reflecting the fact that given low values of time, congestion reduction may not fully compensate for the fee.

time, and trip purpose and mode used. The 2010 survey contains 46,900 households, 116,142 individuals, and 253,648 trips, while the 2014 survey contains 40,005 households, 101,827 individuals, 205,148 trips. [13]

Our analysis focuses on work commuting trips (home to work, and work to home), likely to be the most important trips in housing purchase decisions. These trips accounted for 53% and 59% of all remaining trips, and 62% and 75% of total daily travel distances in 2010 and 2014, respectively. Table 1 provides summary statistics for variables related to individuals, and trips by survey year. Household income increased dramatically with the share of the lowest income group ($<$ 50k annually) decreasing from 48 to 18 percent during 2010-2014 while the shares for the high income groups grew. Vehicle ownership increased from 44 to 62 percent. Other individual attributes are similar across the two waves. Both the share of respondents living within the 4th ring road and that working within the 4th ring road decreased by about 10 percentage points from 2010 to 2014, reflecting the increased spatial dispersion of housing and job locations.

In terms of the work trip variables, each record reflects a single home-to-work or work-to-home trip. There are six main trip modes: *Walk*, *Bike*, *Bus*, *Subway*, *Car*, and *Taxi*.[14] The bus and subway trips could include walking segments while the walking trips are only constituted by walking as described below. The travel time and travel (out-of-pocket)costs are for the chosen modes. The travel time decreased while the travel cost increased from 2010 to 2014. The shares by mode and the changes in travel pattern are further shown in Figure 3 and discussed below.

To estimate mode choice demand in Section 5.1, we need attributes for all modes in a commuter's choice set, though we only observe a single mode in the travel survey, the one taken. As a result, we construct counterfactual trip times and costs for commuting for six modes and validate our calculations using information from reported trips. In principle, many modes are possible, but we construct a commuting choice set to include six modes for a trip: *Walk*, *Bike*, *Bus*, *Subway*, *Car*, and *Taxi*. More details on the rationale for this set and the full procedure for construction of the data are provided in Appendix B.2.

To calculate counterfactual travel times and distances, we use Baidu Maps API for walking, biking, car and taxi. Baidu maps incorporates congestion prediction based on the time of day and day of week, so we match the time stamp in API calls to departure times from the travel survey. Since average congestion may be different when the API calls were made relative to when households were surveyed, we adjust predicted travel times based on the annual traffic congestion index, which is defined by regions in Beijing. Bus time predictions from Baidu do not provide information about the number of transfers and walking time between bus stops, which can be substantial for longer trips. For this reason, we use a different API, Gaode Maps. For subway commuting, an API will not account for changes in the subway network, a key aspect of our simulation approach, so we use subway maps in GIS to reconstruct the historical subway network for the

[13] We further drop trips with ambiguous origins and destinations which cannot be geo-coded (40%), trips on weekends and holidays (10%), trips of the elderly and kids (age> 65 or age <16, 12%), and trips with clear errors (6%). Eventually we are left with 78246 trips by 29770 individuals in the year 2010 and 98730 trips by 38829 individuals in the year 2014.

[14] There are additional modes in the survey including motorcycles, company shuttles, and unlicensed taxis, and combination of several modes. They collectively account for less than 3% of the all trips and are dropped in our empirical analysis.

time period in question.[15] From these maps, we calculate subway travel times from station to station using published time schedules of subway lines.

Figure 3 provides information on the observed shares of each mode, as well as the *constructed* travel time, cost, and distance by each mode for commuting trips (see Appendix B.2 for details). Panel (a) shows the data for 2010 and 2014 separately. There are several notable patterns. First, walking accounted for a significant share of all commuting trips: 15.0% ad 13.5% in 2010 and 2014, respectively. These trips took about 51 and 40 minutes on average with a distance of 4.9, and 3.7 kilometers. Second, from 2010 to 2014, the shares of walk, bike, and especially bus saw a reduction while the share of car (i.e.,self-driving) and subway trips increased, reflecting the increase in vehicle ownership and the expansion of the subway network. Third, walking and subway trips were the longest in duration while the subway and car trips were longest in distance. While car trips are slightly longer and farther than taxi trips, they are cheaper. The tradeoff between time and cost is clear: trips by walking are slowest but also the cheapest. Car and tax trips are faster but more expensive than other modes.

Panel (b) of Figure 3 shows the data by high-and low-income groups. High-income households are more likely to drive, use subway, and take taxi while less likely to use other modes, compared with low-income households. As a percentage of hourly wage, car and taxi trips are much more expensive for low-income households than for high-income households. In terms of travel distance, there is very little difference across the two income groups except among car trips. This is consistent with the lack of strong income-delineated residential pattern observed in the housing data below.

3.1.2 Housing Transactions Data

Data on housing transactions come from a government-backed mortgage program, a major program in the mortgage market in Beijing during the sample period from July 2006 to July 2014. As is reflective of the supply of housing in much of urban China, almost all of the housing units in our data are within housing complexes analogous to condominiums in the United States. As part of the social safety net, the mortgage program aims to encourage home ownership by offering prospective homeowners mortgage with a subsidized interest rate. Similar to the retirement benefit, employees and employers are required to contribute a specific percentage of the employee's monthly wage to a mortgage account under this program. The savings contributed to this account can only be used for housing purchases and rental during the employment period with the employer. Determined by the Ministry of Housing and Urban-Rural Development, the subsidized interest rate under the program is about 30% lower than the commercial mortgage rate for all eligible borrowers. Virtually all home buyers would apply for this mortgage first before going to other loans. There are no refinancing observations in the sample and therefore, each mortgage contract refers to a housing transaction.

The final data set includes 79,884 mortgage transactions and Table 2 provides summary statistics of the

[15] Our calculations assume that travelers walk to the nearest subway station from their origin and from the nearest to their destination. These walking distances and times are calculated with Baidu Maps API.

data.[16] The mortgage data include information on household demographics including income, age, marital status, residency status (*hukou*), and critically for our analysis, the address of the work location for primary and if present, co-borrowers. The data also contain information on housing attributes such as size, property age, the street address of the property newly purchased, the transaction price, and the date when the mortgage was signed. We geocoded the home and work locations in the data. Appendix B.3 presents a discussion on the distance of work commute by gender and the representativeness of the mortgage data. In addition, we obtain data on the location of "signature" elementary schools and parks in Beijing, both of which capture important amenities in housing decisions. The locations of these schools and parks are depicted in Appendix Figure A9.[17] The signature schools are concentrated within the 4th ring road while the parks are more dispersed across the city.

Because the mortgage data represent a subset of housing transacted in Beijing and may be subject to selection issues, We re-weight the mortgage data based on a much larger and more representative housing data set. This larger data set includes about 40% of all transactions in Beijing's second-hand market during our data period from the largest real estate brokerage company, Lianjia, present throughout the city and across housing segments. The larger data set also includes all new residential property sales based on real property registration from Beijing Municipal Commission of Housing and Urban-Rural Development.[18] Different from the mortgage data, the housing transactions in this larger data set do not include information on the work location of the owners, therefore preventing us from using it for the main empirical analysis. To improve the representativeness of the mortgage data, we match the distributions of housing price, size, age, and distance to city center of the mortgage data to those in the larger housing data using entropy balancing (Hainmueller, 2012). The procedure is described in Appendix B.3 and makes the mortgage data representative of the broader Beijing housing market. We use the weighted sample in our benchmark analysis and the unweighted sample in robustness checks.

Figure 4 shows the spatial pattern of housing and household attributes by TAZs from the mortgage data. The sample averages are based on housing transactions in the corresponding TAZ from 2006 and 2014, and a warmer color representing a higher value. Panels (a) and (b) make clear that housing prices tend to be higher in the city center while housing size smaller as predicted by the classical monocentric city models. Panel (c) shows that distance to work is shorter for those living close to the city center, reflecting a higher concentration of jobs closer to city center. There are exceptions: some TAZs in the northwest part of the city outside the 5th ring road exhibit short work distance, due to the high-tech center in that area as shown in A10.[19] Relative to

[16] We remove transactions with missing or zero reported price, price per square meter less than ¥5,000, buyers with no reported income, and an address outside of the 6th ring road. The data set for the structural analysis is slightly smaller than this as we lose some data in constructing the choice set.

[17] There are 65 signature schools in Beijing and they are designated by the Beijing municipal government as the top schools among all elementary schools in Beijing. These schools have better resources and better student performance. The enrollment in these schools in most cases guarantees a seat in the the top middle schools and subsequently top high schools.

[18] The new sales data include "commercial residential properties", accounting for about 90% of all new property sales. The data do not include transactions for employer-provided or subsidized housing.

[19] Appendix Figure A10 shows that Beijing is not actually monocentric. There are several large job clusters across the city, notably, a high-tech cluster towards the northwest between the 3rd and 5th ring roads and a financial cluster between the 2nd and 4th ring

panels (a)-(c), the pattern of household income in Panel (d) is more mixed. There are examples of relatively high income households between the 5th and 6th ring roads in the central north and the northeast. Some high-income households opt to live in larger properties with lower unit price in these areas, reflecting the classic distance-housing size tradeoff illustrated in the monocentric city model in Section 2. In general, high-income households tend to live in the northern parts of the city, consistent with better amenities and more jobs in these areas shown in Appendix Figures A9 and A10.

To incorporate commuting into housing decisions, we need to construct work commute attributes (i.e., time and out-of-pocket costs) of different travel modes in a manner similar to the travel survey. This would allow us to construct the ease-of-commute measure for a given house-job pair. In theory, one could construct the attributes of different travel modes for each potential housing choice for a given borrower/job location as illustrated in Appendix Figure A7. However, this is not technically feasible given the large number of housing units available on the market at a given point in time and the limitations on Baidu and Gaode API calls. The large size of the housing choice set is a common empirical challenge in the housing demand literature, and in our case, it is further compounded by the fact that there are multiple travel modes associated with each potential housing choice. To reduce the computational burden, we use a choice-based sampling strategy to limit the size of the housing choice set following McFadden (1978), Wasi and Keane (2012), and Guevara and Ben-Akiva (2013). The choice set for a given transaction in the mortgage data is composed of the purchased property and a one percent sample of properties randomly chosen from those sold during a 60-day window (30 days before and after) around the purchase date. Beijing's real estate market was fluid during our data period: the average days-on-market for a property was 50 in 2012 and it took a buyer on average 40 days to purchase a property.[20] Our results are robust to other reasonable time windows in defining the choice set. For each property in the choice set, we then construct travel mode attributes for the work commute of the male borrower and the female borrower, respectively, based on their respective job locations. The construction of the mode choices involves over 13 million route-mode combinations.

3.2 Reduced-form Evidence

Before proceeding to the structural sorting model, we examine whether the capitalization of changes in the transportation system into housing prices to be large and whether residential sorting in response to these changes is meaningful. To illustrate these effects, we examine the effect of the car driving restriction policy (CDR) on the housing market using a reduced-form approach. The CDR started in July 2008 and prohibited car-owners from driving one day a week based on the last digit of their license plates. Two principal effects might be expected in response to this policy: adjustment in travel choices, specifically towards public transportation and relocation of residential location. Building on the urban literature, we may expect the restriction to induce greater demand for properties closer to public transportation, increasing the price of these proper-

roads on the east side of the city.

[20]See https://zhuanlan.zhihu.com/p/221809466 and http://xinhuanet.com/fortune/2020-01/07/c_1125428787.htm for references.

ties. This could mean that wealthier households, with potentially higher values of time, sort into these units: so-called transit-induced gentrification.

Figure 5 shows scatter plots before and after the CDR of unit home prices (in ¥1,000 per square meter) relative to the distance of these properties to the nearest subway station.[21] The total panel reports the unit price of a property against its distance to the nearest subway station from the raw data. The bottom panel shows residualized plots after controlling for year-by-month and neighborhood fixed effects.[22] Both panels show that the price gradient becomes steeper after the policy, suggesting that properties close to subway command a higher price premium after the policy. Additional evidence from regression analysis are provided in Appendix Section C. Consistent with theoretical predictions, the driving restriction increases the price premium of the properties near subway stations.

Appendix Section C also presents a reduced-form analysis for residential sorting by regressing the distance to subway and work on the interaction between the CDR dummy with household income. The results show that the driving restriction policy reduced the distance to the nearest subway station and work more for high income households. This provides suggestive evidence to support the hypothesis that high-income households sorted closer to these locations and low-income households sorted away, potentially because they were priced out. While these results confirm the importance of the capitalization and sorting in response to transportation policies, they do not adequately capture important preference and spatial heterogeneity. We now turn to an equilibrium sorting model of housing and commuting mode demand in order to capture the channels by which transportation policies affect these choices and to analyze the efficiency and equity impacts of different policies in the unified framework.

4 Empirical Sorting Model

We first lay out an empirical equilibrium sorting model that incorporates commuting choices into housing decisions. The commuting choices are affected by traffic congestion which is endogenously determined by both household location and travel choices. After we describe the model, we then discuss identification and estimation of model parameters.

4.1 Model Overview

The sorting model posits that utility-maximizing households choose housing based on their preference for housing attributes, and neighborhood amenities (e.g., school quality). The aggregation of individual choices affects the supply of neighborhood amenities (Epple and Sieg, 1999; Kuminoff et al., 2013). For example, if a

[21] We focus on two years before and two years after the starting date of the program in balancing the tradeoff between the sample size and the potential for confounding changes in housing and transportation.

[22] A neighborhood is defined as a Jiedao, an administrative unit similar to a census tract and with the average size being about 2.8 square kilometers. Each district of Beijing contains an average of 35 Jiedaos. We use Jiedao to denote neighborhoods where properties share similar observed and unobserved amenities. Appendix Figure A11 illustrates the configuration of Jiedaos relative to housing units, ring roads, and subway lines in Beijing.

large number of high-income households choose to live in a neighborhood with desirable amenities such as access to schools with higher test scores, the quality of the school would be likely to be affected by changes in the composition of students. By allowing for the endogenous formation of these amenities and equilibrium feedback effects, equilibrium sorting models have proven to be powerful tools in understanding the distributional and general equilibrium impacts of the policies.

The amenity that our analysis focuses on is traffic congestion: on the one hand, it affects individual commuting and housing choices, and on the other hand, it is determined by these individual choices in the equilibrium. Our equilibrium sorting model parameterizes the determinants of individual commuting and housing decisions, and specifies equilibrium conditions for traffic congestion and the housing market. The estimation identifies consumer preferences by matching model predictions to choice outcomes from our data. The equilibrium nature of the model also allows for post-estimation counterfactual simulations, providing an empirical form of comparative statics analysis of prices, locations, and the level of amenities from marginal or non-marginal policy changes. A key assumption underlying our approach is that, after accounting for location and demographic differences, preferences for commuting mode choice from the travel survey are representative of those for home buyers in the mortgage data.[23]

The empirical sorting literature typically use the distance from home to CBD to capture how work commute affects housing choices. This practice could conflate commuting costs with other unobserved attributes that households may value (e.g., unobserved neighborhood quality) and it ignores the role of the availability of commuting options between locations. In addition it does not allow equilibrium feedback effects from traffic congestion to housing demand: changes in traffic congestion could affect commuting time and hence the attractiveness of a property even if the physical distance to CBD has not changed. Instead, we characterize the location attractiveness of a property in terms of work commute using the expected utility from the optimal travel mode between home and job locations, taking into account of available public transit, road conditions, and transportation policies. Our sorting framework is a two-stage nested model. The first stage (or the inner nest) is a model of travel mode choices, which generates the expected utility from the optimal travel mode, or the ease-of-commute measure for a given house-job pair. The second stage (or the outer nest) is a model of housing choices which takes the ease-of-commute measure as one of the observed household-specific housing attributes.

The choice of housing location could be part of a joint decision of work and home locations. The joint decision may be simultaneous or sequential, but the levels of endogenous amenities could affect both choices following Rosen (1979) and Roback (1982). However, we take job locations as given in our analysis for three reasons. First, 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. Second, jobs in the same industry tend to be clustered in Beijing and job switching may not imply meaningful changes of job location. Third, from the empirical standpoint, the mortgage data provide information on locations of housing and current employment, but do not

[23] A large literature in environmental economics considers conditions under which the approach of transferring preferences for non-market amenities is valid (Boyle and Bergstrom, 1992; Rosenberger and Loomis, 2003).

have information on job searching (e.g., available jobs at the time of searching). Therefore, incorporating job location decisions would necessitate additional data. Similarly, we do not model firm locations, which could be affected by transportation policies in the long run. Our analysis therefore does not model the potential positive spillovers from the agglomeration of firms as modeled in the recent studies using the quantitative spatial models. [24]

The emerging literature using the quantitative spatial models have made considerable advances in modeling the joint processes of job and residential locations. Changes in the transportation system could translate into productivity improvements (through changes in the allocation of time and labor market matching), a margin of adjustment not incorporated in our model. This literature use observed worker flows and wages and applying a gravity equation framework to recover iceberg commuting costs. However, with few exceptions (Fajgelbaum and Gaubert, 2020), this literature tends to recover the cost of commuting through an origin-destination-specific disamenity rather than incorporating individual commuting decisions and congestion externality. While taking job locations as given, our equilibrium sorting framework is able to capture endogenous congestion and the welfare impacts from unpriced externality across commuters under different policy scenarios. [25]

4.2 Housing Demand

We specify a characteristics-based housing demand model, in which preferences over housing are parameterized as a function of observed and unobserved household attributes (Lancaster, 1971; McFadden, 1978; Berry et al., 1995). We use i to index household, and j to index housing choice (i.e., a condo unit). Our data are longitudinal, but we suppress time t to ease exposition. Given a set of observed and unobserved household attributes (which affect preferences) and the work location, utility for household i choosing house j can be written as:

$$\max_{\{j \in J\}} U_{ij} = \alpha_i p_j + \mathbf{x}_j \beta_i + \sum_k \phi_k EV_{ijk} + \xi_j + \varepsilon_{ij}, \tag{2}$$

where J is the choice set for household i and the construction of the choice set is discussed below. $k \in \{Male, Female\}$ denotes members in the household with commuting needs. We henceforth suppress subscript k for the ease of exposition, but include EV terms for both members in subsequent formulations. α_i is the

[24] Diamond (2016) is a micro-founded study that bridges this gap by incorporating housing and labor markets into the evaluation of the heterogeneous welfare consequences of the movement of workers between US cities, although without endogenizing congestion from the transportation sector.

[25] Another potential limitation of the quantitative spatial model is that welfare improvements only result from changes in real income due to gains from trade via an increase in market access. This benefit is mediated directly through the elasticity of imports with respect to variable trade costs (Arkolakis et al., 2012). In the context of urban transportation, this seems potentially limiting as spatial mismatch or wasteful commuting due to pre-existing distortions, like congestion, may leave open opportunities for Pareto improvements without a change in the level of market access.

individual-specific price coefficient and related to the log of household income y_i:

$$\alpha_i = \alpha_1 + \alpha_2 * ln(y_i).$$

p_j is the price of house j. $\mathbf{x}_j$ is a vector of housing attributes such as housing size and the number of bedroom. β_i is a vector of household preference over other housing attributes and we specify them as a function of observed household demographics. The marginal utility for each housing attribute can be separated into an individual-specific component and a population-average component, i.e., for each element s in β_i:

$$\beta_{is} = \bar{\beta}_s + \mathbf{z}_i \beta_s,$$

where $\mathbf{z}_i$ are household demographics. ξ_j captures unobserved attributes that affect consumer choices. ε_{ij} is an i.i.d. error term that captures unobserved preferences over each housing choice.

EV_{ij} is the expected utility from the best commuting alternative and it characterizes the attractiveness of the property in terms of work commute. This ease-of-commute term is constructed from a discrete choice model of travel mode that we describe below. Note that EV_{ij} is affected by the congestion level, which is determined in the equilibrium by travel mode choices and location choices of all households. This term is the key innovation relative to residential sorting models that incorporate commuting based on fixed distances discussed earlier. This term allows for joint consideration of the set of transportation policies that affect commuting costs heterogeneously across individuals and houses. We also allow ϕ_k to be heterogeneous by estimating random coefficients

$$\phi_{kr} = \bar{\phi}_k + \phi_k \nu_{kr}, k \in \{Male, Female\}, \text{ and}$$
$$\begin{pmatrix} \nu_{male,r} \\ \nu_{female,r} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}\right].$$

4.3 Travel Mode Choice

Utility-maximizing individuals within a household choose a commuting mode based on the time and financial cost associated with each mode in M_{ij} = {Walk, Bike, Bus, Subway, Car, and Taxi}.[26] Preferences for particular attributes of travel modes vary across individuals, 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 random coefficients to account for these considerations. Individual i's utility of commuting to work from

[26] For the purpose of our analysis we consider the mode choices of individuals as independent because of limited information from which to consider joint decisions. When it comes to housing location, we are also modeling hypothetical commutes, for which the exact process of trip-chaining is not likely to be ex-ante clear to most households. Rather they may have a general sense of the relative cost of commuting for one house relative to another as specified in the EV term.

house j using mode choice m is specified as:

$$\max_{m \in M_{ij}} u_{ijm} = \theta_m + \gamma_{1i} time_{ijm} + \gamma_2 cost_{ijm}/y_i + \mathbf{z}_i \eta_m + \varepsilon_{ijm}, \tag{3}$$

where M_{ij} is the set of transportation modes available to individual i. θ_m is a mode-specific random coefficient of a normal distribution with mean μ_m and variance σ_m. θ_{walk} is normalized to zero. These random-coefficients capture heterogeneous mode-specific (dis)amenities, scheduling or inconvenience costs that do not scale with the time or distance traveled. Variable $time_{ijm}$ denotes the duration of work commute between house j and i's job location using mode m. Travel time from driving $time_{ij,car}$ is affected by the congestion level on the road, which itself is an equilibrium outcome determined simultaneously by the spatial distribution of the households and the travel modes of all households. We also allow time preference γ_1 follows chi-square distribution with degree of freedom equal to three and mean at μ_γ to capture heterogeneous time preferences. The monetary cost of the trip is denoted as $cost_{ijm}$, and ε_{ijm} is the i.i.d. error term.

The way in which time and monetary costs enter this utility function makes it straightforward to calculate the value of time (VOT), which is $\frac{\gamma_{1i}}{\gamma_2} \cdot y_i$. This specification allows the financial burden of travel to scale with income and VOT can be conveniently expressed as a share of hourly income. VOT is a fundamental concept in transportation analysis and its empirical measurement is crucial for travel demand analysis and the evaluation of public policies. Under the time allocation framework of Becker (1965), the travel time should be valued relative to the after-tax wage rate assuming that time can be freely transferred between work and non-work activities (e.g., leisure or travel).

EV_{ij} in equation (2) is defined as the following:

$$EV_{ij} = \mathbb{E}_{\varepsilon_{ij}} \left(\max_{m \in M_{ij}} u_{ijm} \right), \tag{4}$$

where the expectation is over the set of i.i.d. draws ε_{ijm} across travel modes. If ε_{ijm} has type I extreme value distribution, the EV term admits the convenient log-sum form (up to a normalizing constant):

$$EV_{ij} = \log \left(\sum_{m \in M_{ij}} \exp \left[\theta_m + \gamma_1 time_{ijm} + \gamma_2 cost_{ijm}/y_i + \mathbf{z}_i \eta_m \right] \right). \tag{5}$$

4.4 Market Clearing Conditions and the Sorting Equilibrium

In the following, we define the market clearing conditions and the sorting equilibrium. Intuitively, there are two interrelated markets in our model: the housing market, and the implied market for driving. In the housing market, the choices of individual households aggregate to housing demand, and housing prices adjust to equate demand and supply. In the market for driving, the congestion level on the road affects driving time, which then affects driving demand through individuals' travel mode choices. Commuters consider the average cost of driving when making mode choice decisions despite the fact that they are affected by the marginal social cost, including congestion externalities. The two markets interact in two dimensions: the spatial location of households affects the distance of home-work travel, the travel mode, and hence the market for driving. At the same time, the level of traffic congestion determined in the market for driving affects the attractiveness of residential locations through their 'matching value of home-work commute' as discussed above, and in turn the spatial distribution of households.

Commuting Mode Choice The sorting equilibrium consists of equilibrium in two related markets. In the sorting equilibrium, travel decisions are conditional on a housing location i given work location j, which is determined by probability P_{ij}.

We start with travel mode choices and the market for driving. Conditional on home location j, the conditional probability of household i choosing mode m for work commute is defined as:

$$R_{ijm}|i,j = r(\mathbf{z}_i, \mathbf{w}_{ijm}, v_{ij}), \tag{6}$$

where $\mathbf{z}_i$ is a vector of household demographics such as household income. This conditional probability is constructed based on mode-specific indirect utilities from (3) and the choice of home locations inherent in P_{ij}. $\mathbf{w}_{ijm}$ is a vector defines the travel time and fare cost between i and j for each mode m:

$$\mathbf{w}_{ijm} = [\Xi_{ij}, \quad \theta_{im}, \quad cost_{ijm}/y_i, \quad time_{ijm}]. \tag{7}$$

$\mathbf{w}_{ijm}$ also includes the term Ξ_{ij}, which is a $J \times J$ matrix of ones and zeros defining the choice of house j for each household i given location choice probability P_{ij}, which is defined in the next subsection.

Finally, we use v_{ij} to denote the speed for driving between i and j, which together with the driving distance determines the travel time for driving.[27] If the error terms in equation (3) have an extreme-value distribution, then the choice probability R_{ijm} admits the convenient logit form. The aggregation of individual choices gives rise to the aggregate demand for driving.

The speed of driving v_{ij} is a constraint on the supply of travel times for car commuting in Beijing. The negative relationship between driving speed and traffic density gives rise to a congestion externality, because the driving decisions of others reduce the speed of travel for household i. Figure 1 depicts the congestion externality and the equilibrium congestion level determined by (6).[28]

Here v_{ij} is continuous function that reflects congestion from the mode choices of all commuters given their housing choices and therefore is non-decreasing in the number of car-commuters on roads between home location j and work location i.[29] It therefore is determined via the attributes of each mode option as

[27] $v_{ij} = \frac{dist_{ij,drive}}{time_{ij,drive}}$. Note this also means that $time_{ijdrive}$ in w_{ijm} is determined by v_{ij}.

[28] Congestion on the road affects travel times for bus in addition to driving and taxi, however this effect is more complicated as it depends on the time for entering and exiting the approach for bus stops, which depends on very local characteristics of the roadway. For the purpose of our analysis we treat buses as if they were in dedicated lanes unaffected by congestion, which may result in a an under-prediction of bus mode shares from our estimates.

[29] This relationship is implicit in our estimation and is a potential source of endogeneity discussed in the next section. In section 6

well as the set of mode choices: $(\mathbf{w} = \{w_{ij}\}_{i,j}, \mathbf{R} = \{R_{ij}|i,j\})$:

$$v_{ij} = v_{ij}(\mathbf{w}, \mathbf{R}). \tag{8}$$

Housing Choice The probability of household i choosing house j is determined by the distribution of random utility as specified in the housing demand model and is denoted as:

$$P_{ij} = h(\mathbf{z}_i, \mathbf{EV}_i, \mathbf{p}, \mathbf{X}, \boldsymbol{\xi}), \tag{9}$$

where $\mathbf{EV}_i$ is a vector of expected utility from the optimal travel mode between job i and each of potential home locations. $\mathbf{p}$, $\mathbf{X}$, $\boldsymbol{\xi}$ are prices, observed and unobserved attributes of all housing choices on the market. $\mathbf{EV}_i$ links the housing market with the driving market, whose element is defined as:

$$EV_{ij} = e(\mathbf{z}_i, w_{ij}, v_{ij}). \tag{10}$$

The aggregation of individuals' choice probabilities P_{ij} gives rise to the aggregate housing demand. Prices adjust to equate housing demand D_j and supply S_j so that:

$$D_j = \sum_i P_{ij} = S_j, \forall j. \tag{11}$$

Sorting Equilibrium A sorting equilibrium is defined as a set of housing choice probabilities $\{P^*_{ij}\}$, the vector of housing prices $\mathbf{p}^*$, a set of travel choice probabilities $\{R^*_{ijm}\}$, and speed, $\{v^*_{ij}\}$, that reflects endogenous congestion levels such that:

1. The travel market clears according to equations (6) and (8), and

2. The housing market clears according to equations (9) and (11).

Our model follows the class of equilibrium horizontal sorting models with local spillovers studied in Bayer and Timmins (2005) and more closely in Bayer et al. (2004). If ε, the error term in housing equation (2), and ε, the error term in commuting mode choice equation (3) are from continuous distributions (such as type I extreme value distribution used here), then the equation system ((6), (8), (9), and (11)) is continuous. The existence of such a sorting equilibrium follows from Brouwer's fixed point theorem. Intuitively, a unique vector of housing prices (up to a scalable constant) $\mathbf{p}^*$ solves the system of equations defined by equations (9) and (11), conditional on a set of observed and unobserved housing attributes ($\mathbf{X}$ and $\boldsymbol{\xi}$) as well as EVs. At the same time, (6) and (8) implicitly define traffic speed $\mathbf{v}$ as a continuous mapping of a compact and convex set. Any fixed point of this mapping determines EVs and is associated with a unique vector of housing prices $\mathbf{p}^*$, housing choice probabilities $\{P^*_{ij}\}$ and travel choice probabilities $\{R^*_{ijm}\}$, that collectively satisfy the two conditions for a sorting equilibrium.

we model it explicitly.

In this class of sorting models, the presence of a negative spillover due to traffic congestion leads to a unique equilibrium. In the simplest example when the driving speed is uniform across all locations (though the speed level negatively depends on the density of cars), this is a traditional demand system with a unique allocation (choice probabilities), as shown in Berry (1992). With heterogeneous congestion effects that differ across space, one can show that the equation system ((6), (8), (9), and (11)) remains a contraction mapping, and hence accommodates a unique fixed points (i.e., a unique equilibrium).[30] It is worth noting that if there are positive spillovers (e.g., agglomeration effects), uniqueness is not guaranteed. Sufficiently strong positive spillovers could alter the rank-order of the location choices and give rise to multiple equilibrium.[31] A proof of existence and uniqueness is provided in Appendix D.

4.5 Identification and Estimation

Choice Set We first expand on the construction of the housing choice set discussed in Section 3.1.2. Computational and data limitations often, and in our case, require a restriction on the number of alternatives included for empirical estimation. Nevertheless, overly restrictive culling of the choice set can be problematic as documented by Banzhaf and Smith (2007). While it may be logical to restrict the choice set to a set of affordable or nearby properties, this literature suggests that this approach may unnecessarily bias estimation due to unobserved heterogeneity in the choice set definition, and so we eschew any restriction of the choice set based on attributes. In our implementation, we rely on choice-based sampling by taking one percent random sample from properties on the market 30 days before and after the sale date of the chosen property.[32] Beijing's housing market is very fast-moving so that a 60-day window reflects properties of potential consideration by home buyers in our data. The consistency of choice-based sampling methods in multinomial logit and mixed logit models is formalized in McFadden (1978), Wasi and Keane (2012), and Guevara and Ben-Akiva (2013).

Identification & Estimation in Travel Mode Model To estimation of the parameters specified in the housing demand and travel choice models follows a two-stage process. In the first stage, we estimate the mode choice model via simulated maximum likelihood estimation (MLE) based on household travel survey data. The key parameters of interest are preferences for time and monetary costs. We include mode-specific random coefficients to control for mode-specific (dis)amenities or qualities that do not scale with the time or distance traveled. To further control for unobservables that could be correlated with travel time and monetary costs, the model also includes mode-specific fixed effects interacting with year fixed effects, district fixed effects, and household demographics (income categories, age). These interactions control for a rich set of time-varying and location specific unobservables by travel mode.

[30]The proof follows Bayer and Timmins (2005).

[31]In the presence of positive spillovers, the unique equilibrium is more likely to arise with strong consumer heterogeneity, weak spillover effects, or a larger number of choices (Bayer and Timmins, 2005).

[32]To reduce the computational burden, we treat each year as a distinct market and this allows us to conduct the contraction mapping year by year. The average size of the choice set is 27 with a range of 3 to 56. We drop households with a choice set less than 5.

The key identification assumption in estimating mode choices is that the error term is not correlated with time and monetary costs. This assumption would be violated if, for example, the route-specific quality of public transit service (e.g., in terms of delay, comfort, or safety) is correlated with the route-specific monetary cost or travel time. Cost is likely to be exogeneous because the public transit is run by Beijing's public transit authority which sets bus and subway fares according to a uniform rule across all routes. Although some bus or subway routes are more congested than others, the fares do not vary by the level of congestion on-board. In addition, time is unlikely to correlated with unobserved shocks because during our sample period (2010 and 2014) real-time traffic apps are not widely used so people may be more likely to make travel decisions based on ex-ante estimate of travel time. This ex-ante estimate is orthogonal to the realization of traffic shocks on a particular day, in their decision process.

Identification & Estimation in Housing Location Choice Model In the second stage, we first construct EV_{ij} for any j in the choice set of household i using the logsum expression in Equation (5) and parameter estimates from travel mode choices. This step consists of a large set of EV_{ij}, one for each home-work pair, including pairs between i's work location and houses that he/she did not choose but considered. The calculation of EV_{ij} is computationally intensive, requiring us to construct travel time and cost for all available modes for each house location, following the discussion in the household travel survey and Appendix Figure A7. While the application of this two-stage approach to residential sorting is new to our knowledge, similar approaches of nesting the logsum values from random utility models have been used by Capps et al. (2003) and Phaneuf et al. (2008) in healthcare and recreational demand respectively. The estimated $\hat{EV}_{ij}$ enters the housing choice model as an observed housing attribute.[33]

The parameters in the housing demand model themselves are estimated using a two-step procedure, with the first step being a simulated MLE with a nested contraction mapping and the second step being a linear IV/GMM. The two-step strategy follows Berry et al. (1995) and Bayer et al. (2007) in order to address unobserved attributes that could be correlated with housing prices. Unobserved attributes (e.g., quality) ξ_j in Equation (2) could render the price variable endogeneous and bias the price coefficient toward zero. The nested contraction mapping algorithm isolates price endogeneity into a linear framework which permits the usage of the IV strategy. We re-organize Equation (2) as follows:

$$U_{ij} = \mu_{ij}(\theta_2) + \delta_j(\theta_1) + \varepsilon_{ij} \tag{12}$$

$$\mu_{ij}(\theta_2) = \alpha_2 ln(y_i) p_j + \sum_k X_{jk} z_{ik} \beta_k + \phi_m EV_{ijm} + \phi_f EV_{ijf} \tag{13}$$

$$\delta_j(\theta_1) = \bar{\alpha} p_j + \mathbf{x}_j \bar{\beta} + \xi_j. \tag{14}$$

The utility function is re-written as a sum of household-specific utility μ_{ij} and mean utility (or alternative-specific constants) δ_j which absorb variation from unobserved housing attributes ξ_j. The simulated MLE

[33]Because $\hat{EV}_{ij}$ is estimated in the first step, we use the bootstrap method to estimate the correct standard errors in the housing demand model.

with a nested contraction mapping estimates household-specific parameters (θ_2) and mean utilities (δ_j). The log-likelihood function is defined as

$$\begin{aligned} ln\mathscr{L}(\theta_2,\delta_j) &= \sum_i \sum_j \mathbb{I}^i_j lnP_{ij}(\theta_2,\delta_j), \text{ where} \\ P_{ij}(\theta_2,\delta_j) &= \frac{\exp[\mu_{ij}(\theta_2)+\delta_j]}{\sum_h \exp[\mu_{ih}(\theta_2)+\delta_h]}. \end{aligned} \tag{15}$$

$\mathbb{I}^i_j$ is an indicator function being one when household i chooses housing j, and P_{ij} is the choice probability. Berry et al. (1995) show that under reasonable assumptions, for a given vector of θ_2, there exists a unique vector of δ_j that can perfectly match the predicted market shares and observed market shares. Therefor, δ_j can be estimated through the nested contraction mapping by matching observed and predicted market shares by inverting shares in each iteration d:

$$\delta_j^{d+1} = \delta_j^d + \ln\sigma_j - \ln\tilde{\sigma}_j(\theta_2,\delta_j^d),$$

where σ_j is observed market share for housing choice j and $\tilde{\sigma}_j$ is the predicted share constructed by calculating:

$$\tilde{\sigma}_j(\delta_j^d;\theta_2) = \frac{1}{N}\sum_i P_{ij}^d(\theta_2,\delta_j^d),$$

where N is the number of potential buyers on the market, which varies over time. In practice, the market share of each housing choice is $1/N$ and the contraction mapping matches the aggregate choice probabilities to a vector of ones, which is essentially the first order condition of the log-likelihood function as shown in Bayer et al. (2007). By controlling for unobserved housing attributes ξ_j using housing fixed effects δ_j, the estimation can produce consistent estimates on household specific parameters θ_2 including the coefficients on price and the EV term, both of which could be correlated with unobserved housing and neighborhood attributes.

Once θ_2 and δ_j are estimated, we then use linear regressions to estimate preference parameters (θ_1) in mean utilities δ_j as specified in Equation (14) using an IV strategy. Following Berry et al. (1995) and more closely Bayer et al. (2007), we instrument for the price variable using three different sets of variables. First, the average housing and neighborhood attributes (excluding price and the EV term) within 3 kilometers outside the same complex sold within two-month time window from a given house. The identification assumption is that the average attributes of housing choices outside the same complex from housing choice j are not correlated with the unobserved housing attributes ξ_j and have no direct effect on the utility from housing choice j. But due to the housing market competition, they are correlated with the price of housing choice j. Consider for example, two identical housing choices in the same neighborhood being sold at two different points in time (or from two different neighborhoods with the same amenities but sold at the same time), prices may be different due to varying intensity of competition (e.g., the availability of other housing choices) on the market faced by the two housing choices at the time of their sales. The second set is the interaction between the first set of IVs and the winning odds of the vehicle licence lottery policy. The winning odds have decreased dramatically from 9.4% in Jan. 2011 to 0.7% by the end of 2014. The interaction terms capture the likely impact of license lottery policy on the nature of housing market competition and price setting. The third set is the number of houses sold in the real-estate listing dataset in the two-month time window of a given property, which is also a proxy for market competition.

5 Estimation Results

We begin by presenting estimation results for the commuting mode choice model. Using the parameter estimates from that model, we then construct the logsum value of commuting options for work trips based on home and job locations. Taking the logsum values as the input (e.g., observed housing attribute), we then estimate the housing demand model.

5.1 Commuting Mode Choice

Table 3 presents parameter estimates for six specifications of the multinomial logit model based on work commutes from household travel survey in 2010 and 2014. The first three specifications do not have random coefficients and the heterogeneity only comes from the interaction between the travel cost and income while the last three specifications include random coefficients on travel time to capture unobserved consumer heterogeneity. The value of time is represented as the percentage of the hourly wage, and is defined by the ratio of the parameter on travel time and that on travel cost.

Column (1) starts with including interactions between year dummies (2010 or 2014) and mode-specific constants (car, taxi, bus, subway, walking, and biking). The implied VOT from these estimates about 1.42 times the hourly wage. Column (2) adds the interactions between mode-specific constants and trip characteristics including trip distance and ring road dummies of the trip origin and destination. Trip distance could affect mode choices because important trip characteristics such as uncertainty in travel time will likely scale with the length of a trip. This uncertainty, typically called travel time reliability in the transportation literature, has been shown to be an important factor in travel decisions (Brownstone and Small, 2005; Small et al., 2005; Tseng et al., 2009). Ring road dummies for trip origin and destination may also capture differences in the frequency or quality of the public transit, which could affect travel model choice. Including these sets of interactions dramatically affects the coefficient estimate on the travel cost variable, resulting an implied VOT being 0.32 of hourly wages.

Column (3) further adds the interactions of model-specific constants with household demographics including age, gender, education, vehicle ownership, the number of workers, and household size. Adding these variables greatly improves the fit of the model by better capturing the heterogeneity in mode choices across demographic groups. The VOT estimate is 48% of hourly wage.

Columns (4) to (6) use a chi-square distribution with the degree of freedom of three to approximate heterogeneous preference on travel time following Petrin (2002).We winsorize the top and bottom 5% of the distribution to bound the distribution and to minimize the impact of outliers. The degree of freedom of three provides the best model fit. We estimate the parameter μ which scales the random draws. Column (4) relies heavily on the preference heterogeneity in travel time to explain the variation in mode choices especially for driving and taxi. This leads to an estimate of μ that is negative and large, and implies an implausibly large VOT.

Column (5) adds random coefficients on the mode-specific constants with taxi and walking as the baseline group. We use independent normal distributions to approximate the preference heterogeneity, which captures the impact of unobserved demographics on mode choices. For example, some commuters choose driving or taxi not because of their high VOT but because they may have a strong distaste for other modes or may have an important early meeting to attend. Similarly, some commuters choose walking or biking not because they are cheaper but for their exercise benefit. Adding these random coefficients change the coefficient estimate on travel cost dramatically, suggesting stronger consumer sensitivity to travel cost. The implied average VOT is 76% of hourly wage.

The last specification is our preferred specification with random coefficients on five travel modes (with walking as the base). The dispersion on the preference parameters for all transit modes is quite large, suggesting large heterogeneity for these modes. The average (median) VOT estimate is 75.6% (67.7%) of hourly wage and these estimates are in the range typically found in the recent literature.[34] Using a discrete choice framework similar to ours, Small et al. (2005) estimate the median VOT at 93% of hourly wage for commuters in Los Angeles based on data from both travel surveys and choice experiments. Leveraging the tradeoff between vehicle driving speed and gasoline usage, Wolff (2014) estimates the average VOT of 50% of hourly wage based on traffic speed data in eight rural locations in Washington State. Buchholz et al. (2020) use the tradeoff between wait time and price among users on a large ride-hail platform in Prague and find the average VOT to be equal to users' wage during work hours. Goldszmidt et al. (2020) find an average (median) VOT of 75% (100%) of hourly (after-tax) wage based on a large-scale field experiment by the ridesharing company Lyft in 13 US cities by leveraging the random variation in customer wait time and fare.

5.2 Housing Location Choice

We now turn to the estimation results of the housing demand model described in Section 4.1. We first construct the matching value of home-work commute (EV_{ij}) defined in equation (4) based on parameter estimates from the travel choice model. For each household, we generate this measure separately for the Male (61% main borrower) and the female (39% main borrower) based on the job locations for each of the properties in their choice set.[35] These two variables enter the housing demand as additional household-specific attributes. We

[34] The empirical estimates of VOT vary as they come from different contexts and methodology. In the context of travel demand, the estimates typically range between 30% and 100% of hourly income (Small et al., 2007; Small, 2012). The US Department of Transportation recommends 50% of the hourly income as VOT for local personal trips (e.g.,work commute and leisure but not business trips) to estimate the value of travel time savings (VTTS) for transportation projects (USDOT, 2015).

[35] If any family member is unemployed, we set EV_{ij} for that member to be zero for all properties, effectively ignoring this term in the decision process.

first present the estimation results on household-specific preference parameters from the first stage, and then the results from the mean utilities in the second stage.

Table 4 reports the estimates of heterogeneous preference parameters for three specifications, without the EV terms, with EV terms, with EV terms and allowing random coefficients on them. The coefficient estimates from these three specifications by and large are very similar with the exception of the coefficient on the interaction between age>45 and distance to key schools. Housing price is interacted with household income, which is used as an proxy for household wealth. The interaction itself only captures part of the consumer price sensitivity since housing price also enters the mean utilities (household-invariant utilities). The coefficient estimates on the interaction term from both specifications are positive, implying that high-income households tend to be less price sensitive.

Both EV terms in the second and third specifications have positive and significant coefficients estimates. The log-likelihood value increases substantially from Column (1) to Columns (2) and (3), indicating strong explanatory power of the EV terms. The estimates imply that households prefer properties with better ease-of-commute measures, i.e., more convenient for work trips, for both family members. The coefficient estimates in our preferred specification (3) suggest that an average household is willing to pay ¥31,000 more on a property to save ¥1 in each member's work commute, or ¥180,000 more on a property to save 10 minutes of each member's work commute. The coefficient estimate on the EV term for the female member is 20% larger than that for the male member, suggesting that households prioritize the female member's ease-of-commute relative to that of the male member in housing choices. This is consistent with the descriptive evidence that females tend to live closer to their job locations (See Appendix Figure A14). In addition, there is significant preference heterogeneity across households on the EV terms, e.g., due to unobserved household demographics.

For other household specific preferences, we interact age groups with the distance to the nearest key school to capture the heterogeneity in preference for the proximity to key schools, which are shown in Appendix Figure A9. There are three age groups and the baseline group is those (with the primary borrower) below 30. The two coefficient estimates on the interactions in both specifications have negative signs and suggest that households (with the primary borrower) over age 30 more strongly prefer to be close to key schools. Since the enrollment to these elementary schools is restricted to the residents in the corresponding school district, properties close to these schools command a higher premium. The preference for the proximity to key schools is the strongest among households in the age 30 to 45 group, as they are most likely to have school age children.

We do not observe household size in the housing data. To capture potential heterogeneity on property size due to variation in household size, we use the age of the primary borrower as a proxy and interact age groups with property size. The positive coefficient estimates on the two interactions from both specifications imply that households in the high age cohorts have stronger preference for property size. The group with age over 45 has the strongest preference, likely due to the presence of both children or elderly grandparents living in the household, a common household structure in China.

Turning to the second stage, the results are reported in Table 5 for six specifications. Columns (1) and (2) are from OLS while columns (3)-(6) are from IV regressions. All regressions include district by year-month-district (i.e., month of sample intereatced with district) fixed effects to capture time-varying changes in market conditions and amenities that could vary by district. Columns (2)-(6) also include neighborhood fixed effects to capture unobserved time-invariant neighborhood amenities. We use three sets of IVs for housing prices. The first set includes the average attributes of the properties within 3km outside the sample complex sold in a two-month time window of a given property. The second set is the interaction between the first set of IVs and the winning odds of the vehicle licence lottery policy. The third set is the number of properties sold in the real-estate listing dataset in the two-month time window of a given property. Our preferred specification (6) where all instruments are used, the first stage F- statistics is 14.22, and the overidentification test cannot be rejected at 10% level.

Across all columns, the price coefficient estimate is negative and statistically significant. The IV estimates are smaller than the OLS estimates, consistent with the findings in the industrial organization demand literature that unobserved product attributes tend to bias OLS estimate toward zero.Appendix Table A4. In the second-stage regressions based on the first specification without the EV terms in Table 4, the price coefficient estimates and the price elasticities are smaller in magnitude, consistent with the downward bias due to unobserved attributes. Timmins and Murdock (2007) find a 50% downward bias in the estimation of consumer welfare from recreation sites when congestion on site is ignored in the demand estimation. The implied average price elasticities from OLS are positive due to the positive interaction between income and price coefficient estimate in Table 4. The average price elasticities are -1.5 and -1.7 in columns (4) and (6), suggesting elastic housing demand.

OLS estimates from columns (1) and (2) provide counter-intuitive coefficient estimates on property size for younger buyers (age less than 30), however, the coefficient estimates from IV regressions in columns (3) to (6) are all intuitively signed. The coefficient estimates on the distance to key (elementary) school from both Tables 4 and 5 suggest younger buyers value the distance to key school the most likely due to the current or pending need for elementary schooling while people with no school-age kids do not value distance to key school when purchasing a house. [36]

[36] Appendix Figure A18 depicts the implied income elasticity of housing demand and the income elasticity of marginal driving cost by household income quintiles. The elasticity of marginal driving cost ranges from 0.6 to 0.84 across income groups while that of housing demand ranges from 0.13 to 0.18. We do not know comparable elasticity estimates based on data from China. Comparing with estimates from the US, our estimates on the elasticity of housing demand are somewhat smaller than those from Glaeser et al. (2008) while the elasticity of marginal driving cost is largely consistent with the literature. Using 2003 American Housing Survey, Glaeser et al. (2008) find the elasticity of lot size to be from 0.25 to 0.5 and they argue that these estimates likely provide an upper bound on the true income elasticity of land demand with respect to housing prices. In addition, our elasticity of housing demand is with respect to building (condo) interior size rather than lot size.

6 Counterfactual Simulations

We now utilize the estimates from the housing and travel mode choices to conduct counterfactual simulations to examine five policy scenarios: driving restriction, congestion pricing, subway expansion, driving restriction and subway expansion, and congestion pricing and subway expansion. The first two are demand-side policies while the third is a supply-side policy. The driving restriction scenario follows the actual policy employed in Beijing during our sample: a vehicle is prohibited from driving in one of the five working days. Under congestion pricing, which is hypothetical, we choose congestion charge to achieve the same level of congestion reduction as driving restriction to facilitate comparison. The key difference between these two policies is that driving restriction is a command-and-control approach while congestion pricing is a market-based policy that affects the price that drivers pay. The subway expansion compares the subway network in 2008 and 2014. During this period, the length of the subway network increased from 100km to 486km, with 8 new lines opened for operation. The details of the simulation approach are provided in Appendix E.

6.1 Simulation Results

Before we present results for policy simulations, we first attempt to validate predictions from our structural model by comparing them to 2014 observations in the mortgage data. We simulate the market equilibrium under the 2008 subway network for two scenarios: with and without the driving restriction. We then estimate regressions to examine the effect of the driving restriction on the price gradient with respect to subway access as in Table A1. The dependent variable is log(price per m^2). Subway distance is the observed distance (in km) from the housing unit to the nearest subway station (based on 2008 network). Consistent with the reduced-form evidence in Table A1 based on observed data, the driving restriction steepens the price gradient with respect to subway access. The coefficient estimate on the interaction between subway distance and the policy is -0.01 compared with -0.023 (with a standard error of 0.013) in Table A1.

We first present the simulation results in Table 6 for six scenarios which allow for household adjusting travel mode choices to adjust but not housing locations. These partial equilibrium simulations achieve two purposes: they isolate the direct effect of policies on the transportation system, and they help to clarify what is additional from adding housing choice to policy counterfactuals. Travel mode choices are affected by the equilibrium congestion level which is endogenously determined. Improvements in traffic speed from a congestion-reduction policy could induce additional driving, hence reducing the impact of the policy. The first three columns are under the 2008 subway network, while the next three are under the 2014 subway network, reflecting the effect of subway expansion. Column (1) shows the baseline results while columns (2) to (6) present the differences relative to the no-policy baseline in column (1). Panel A shows the adjustment of the share of mode choices and equilibrium traffic speed under each scenario; Panel B shows key housing market outcomes; and Panel C presents the welfare results. The results are shown separately for two income groups: households with income above the median (rich) and those with income below median (poor) to reflect differences in how each of these groups might be expected to respond following Section 2.

6.1.1 Travel and Housing Choices

Without Sorting Column (2) of Table 6 shows that the driving restriction reduces the driving share by almost six percentage points for high-income households and over three percentage points for the low-income group.[37] Taxi takes up a disproportionally higher share of reduced driving trips relative to other models among both the high- and low-income groups. This suggests that the random coefficients in the travel mode choice model break the IIA property observed in the multinomial logit model. The reduction in driving increases the average traffic speed by 3.54 km/h, a nearly 15% improvement.[38]

We set the congestion price to be ¥1.22/km to achieve the same congestion reduction as that under a driving restriction with sorting. This congestion price turns out to be only 40 cents lower than the optimal congestion pricing without sorting (as shown in Panel (a) of Figure 10). Congestion pricing induces mode shifting in the same directions as driving restriction. There are two key differences. First, congestion pricing reduces driving much less (more) than a driving restriction among high (low)-income households. The large response from the low-income group is driven by the fact that low-income households are more sensitive to travel cost and hence to congestion charges. Second, although the level of congestion reduction is the same under the two policies, the share of driving remains higher under congestion pricing. The longer driving trips are disproportionally more affected by congestion pricing given that the policy is distance-based.

Column (4) presents the impact of subway expansion from the 2008 network to the 2014 network. The expansion dramatically increased subway access for both income groups: the distance to subway is reduced by about 80% for both groups. As a result, the expansion increases subway ridership by 44% and 41% among high- and low-income groups. The substitution is disproportionally more from taxi and bus trips. Comparing the two income groups, the reduction in taxi and driving trips is larger among low-income groups, due to their larger price sensitivity. Overall, the reduction in driving is about one third of that observed under driving restriction and congestion price, leading to a smaller congestion relief. Although the substitution from non-driving trips to subway trips does not alleviate traffic congestion, it does improve welfare by offering better commuting choices for some trips.

Column (5) presents the results from the combination of subway expansion and driving restriction while column (6) shows the combination of subway expansion and congestion pricing. The impacts on driving under each of these two columns are similar to the sum of the impacts from the two individual policies. There are two countervailing forces at play under the combination of a supply-side and a demand-side policies. First, the policies could have redundant impacts in reducing driving trips: some of the driving trips would be reduced under either the supply-side or the demand-side policy, leading to a smaller aggregate impact than the sum of the impacts from individual policies. Second, the supply-side policy could enhance the demand-side

[37] We remove the driving option from the households who own cars in one of five choice occasions. The rebound effect counteracts the policy impact in equilibrium, leading to reductions in driving shares being less than 20%.

[38] Studies show that road pricing has improved traffic speed by 10-30 percent in several European cities including Norway, London, Milan, Stockholm, and Gothenburg (Small and Gómez-Ibáñez, 1998; Olszewski and Xie, 2005; Leape, 2006; Anas and Lindsey, 2011). See Tables 1 and 2 in (Anas and Lindsey, 2011) for a detailed review on congestion pricing schemes and their impacts.

policy in that the larger subway network makes substitution away from driving easier under driving restriction or congestion pricing. Indeed, as the subway becomes an more attractive option, both driving restriction and especially congestion pricing lead to a larger substitution from driving to subway under the 2014 network than the 2008 network.

With Sorting Figures 8 and 9 show the differential impacts of the transportation policies across TAZs in housing prices and commuting distance relative to the no-policy scenario when households are able to sort by residential location. In Figure 8, while both driving restriction and congestion pricing increase the prices of properties that are closer to job centers, the impact is stronger under congestion pricing driven by the distance-based nature of congestion pricing. Housing prices in northwest parts of the city (near job centers) would increase by about 2,000 ¥/m^2 while those in some parts of southeast that are far from job centers and public transit would decrease by 2000 ¥/m^2. Subway expansion has opposite spatial impacts on housing price: the price increase is mainly observed among properties farther away from the city center (so the public transportation is bad prior to the expansion) but along the new subway lines as shown by the green lines in Panel (c). Property prices would increase by as much as 4000 ¥/m^2 in some southwest parts of the city where the prices have been the lowest. Panel (d) illustrates that the price impacts of subway expansion dominate those from congestion pricing.

Consistent with the spatial pattern of price changes, Figure 9 shows the changes in the average commuting distances for residents in each cell relative to those under the no-policy scenario. There is much stronger sorting under congestion pricing than driving restriction. The commuting distance is reduced in almost all TAZs under congestion pricing, suggesting a more efficient match between job and housing locations. However, subway expansion increases commuting distance in almost all TAZs especially along the new subway lines, exacerbating "wasteful commuting". This further separation of workplace and residence from subway expansion is consistent with the evidence in Gonzalez-Navarro and Turner (2018) and Heblich et al. (2020).

To understand the differential impact on property prices with respect to access to subway, Figure 7 plots the the housing price gradient with respect to the subway distance for 2008 subway network, and 2014 subway network, respectively. The bid-rent curve is steeper under the 2014 network (-¥1900/m^2 per km) than 2008 network (-¥700/m^2 per km) because the 2014 network is larger and hence the proximity to this network is more valuable to commuters. The bid-rent curve under the 2014 network shifts down, reflecting the composition change of the properties whereby the subway expansion reaches to cheaper properties farther away from the city center. [39]

[39] Similarly, from Figure A19, we find *change* in the subway price gradient from congestion pricing is larger (-¥80/m^2 per km) than that from driving restriction (-¥10/m^2 per km). While the driving restriction makes properties close to the subway more attractive for everyone, congestion pricing, being a distance-based policy, makes properties close to subway more attractive for those who live far from work, and for those who are sensitive to a cost increase. The differential impact across households from congestion pricing therefore steepens the bid-rent curve more. We also find that the increase in the price premium from subway proximity due to congestion pricing is smaller under the 2014 network than that under the 2008 network under either policy. As the subway network becomes more attractive, fewer commuters use driving as the travel mode under 2014 network, implying less competition for the properties close to the subway.

By incorporating both endogenous congestion and household sorting, Table 7 present several key results in terms of travel modes and housing locations for two income groups. First, sorting has important implications on policy effectiveness in congestion relief. While sorting weakens the effectiveness of driving restriction, it strengthens that of congestion pricing. Sorting introduces two countervailing forces under driving restriction. First, driving restriction incentivizes households to live closer to jobs, hence further reducing congestion on top of what observed in Table 6. Second, congestion reduction from the policy makes driving less costly and hence disproportionally increases driving among those with a large distance to work. As equilibrium congestion is affected by both intensive and extensive margins, the increase in the extensive margin dampens the effectiveness of driving restriction. In contrast, as a distance-based policy, congestion pricing reduces both intensive and extensive margins and generates a larger congestion reduction with sorting.

Second, while each policy leads to congestion reduction, they have different impacts on the spatial distribution of households. Consistent with the reduced-form evidence, driving restriction marginally induces high-income households to closer to subway, while pushing low-income households to move farther away from work and subway. However, congestion pricing, push both high- and low-income groups closer to jobs, hence reducing "wasteful commuting" for both groups. Due to the distance-based nature, congestion pricing induces stronger sorting than driving restriction as illustrated in Figure 9. Driving restriction leads to small changes in commuting distance and in opposite directions across TAZs, but congestion pricing leads to larger reduction in commuting distance in nearly all TAZs. In terms of location relative to subway, high-income households move closer to subway while low-income households move further. The opposite effect on the two groups in terms of distance to subway is in contrast with the effect in terms of distance to work. This is driven by the fact that the subway network is the same for all households and therefore households have to compete for the set of properties in terms of their distance to subway, but job locations differ across households and a Pareto improvement in commuting distance is possible.

Third, despite the large increase in subway usage, subway expansion leads to the smallest congestion reduction. Traffic speed increases by about 7 percent with sorting, only about 40% of what could be achieved from the two demand-side policies. Our estimate is lower than what is implied by recent empirical studies that focus on the short-run impact of the subway system on traffic congestion (Anderson, 2014; Yang et al., 2018; Gu et al., 2020).[40] Our analysis shows that the effectiveness of subway expansion is attenuated by sorting as illustrated in shown in 9: both income groups move farther away from work and commute longer distance. This induced travel demand from transportation infrastructure investment undermines the objective of congestion reduction, a result consistent with the previous literature (Downs, 1962; Vickrey, 1969; Duranton and Turner, 2011).

Fourth, although congestion pricing and driving restriction achieve the same level of congestion reduction

[40] Using a regression discontinuity (in time) approach, Anderson (2014) finds a 47% increase in highway traffic delays during the peak hours from the shutdown of the Los Angeles bus and rail lines for 35-days. Yang et al. (2018) shows that the subway expansion in Beijing from 2009 to 2015 reduces traffic congestion by 15% on average using a 120-day window surrounding subway opening. Using a difference-in-differences framework, Gu et al. (2020) estimate that one new subway line increases traffic speed by 4% during peak hours on nearby roads based on 45 subway lines opened across 42 Chinese cities during 2016 and 2017.

under the 2008 network, congestion pricing is more effective under the 2014 network. That is, the market-based demand policy and the supply side policy exhibit complementarity by producing a stronger aggregate impact.[41] The results reflect two underlying countervailing forces. On the one hand, subway expansion itself increases the attractiveness of using subway and hence reduces the share of driving. This leaves a smaller room for and reduces the impact of demand-side policies among an average driver. On the other hand, the demand-side policy could be more effective in affecting the infra-marginal drivers who now have a better subway network to switch to. The first force appears to dominate under the driving restriction but the second force is stronger under congestion pricing. Congestion pricing affects both the extensive and intensive margins, both of which could be reinforced by the subway expansion.

With Sorting and Supply Adjustment Finally we discuss the results in Table 8 with sorting and additionally allowing supply side to adjust. Housing supply is modeled as a constant elasticity function of local property prices[42]. To fix ideas of how incorporating supply side changes our findings, think about property A whose prices increases after a policy. Now housing supply of property A will increase. Hence in the new equilibrium, we expect part of housing price changes is absorbed by housing supply change. The additional increases in housing supply of attractive houses will allow more efficient sorting, hence magnifying the sorting effects when supply is fixed.

This intuition is verified by our simulation results. In terms of driving speed, supply side adjustment makes congestion pricing policy more effective (from 3.52km/h to 3.72 km/h), while attenuating the gains from subway construction (from 1.44km/h to 1.11 km/h). To see whether the additional changes comes from intensive or extensive margin, it is worth noticing that distance to work under congestion pricing additionally decreases (from -0.28km to -0.48 km for high-income households), while distance to work under subway construction additionally increases (from +0.17km to +0.51km for high-income households). Driving probability, on the other hand, do not change significantly when supply adjustment is allowed. Hence we conclude that the changes in speed should be contributed to intensive margin. In other words, supply side adjustment under congestion pricing increases the housing supply of inner city properties, allowing people to live even closer to their work, shortening their commuting trips, and magnifying the anti-sprawling effects. Supply side adjustment under subway construction increases housing supply of property in suburban areas, forcing people to live further away from their work and exacerbating the sprawling effects. In terms of welfare consequences of supply adjustment, we will elaborate in the next section.

6.1.2 Welfare Analysis

Panel C in Tables 6, 7, and 8 presents the welfare results under the five scenarios, relative to the baseline scenario of no policy and the 2008 subway network. To construct net welfare, we keep a balanced government

[41] As demonstrated in Akbar et al. (2018), the supply-side constraint (poor transport infrastructure) is a key determinant in traffic speed across cities India, highlighting the importance of transport infrastructure provision.

[42] We set the elasticity to be 0.52 following Wang et al. (2012)'s estimates on housing supply elasticity in Beijing

budget under each scenario by either taxation or rebating uniformly across households. Subway construction and operation are funded by a head tax while the revenue from congestion pricing is rebated back lump sum. We will mainly focus on Table 7 as it is our preferred specification.

Since transportation infrastructure such as subway is durable, we assume a 30 year time-span during which the capital cost should be recouped. During the 30-year spend, we calculate total capital and operating costs and apportion 75% of the costs to work commute in our welfare analysis to compare with the changes in consumer surplus as a result of work commute being affected by subway expansion.Work trips account for about 60% of all trips and 75% of the total travel distance in the 2014 travel survey. So what we use (75%) in the welfare analysis is likely to be a upper bound of subway cost. A related issue is the utility function specification where the total housing price rather than rental price is used. So the utility should be considered as a discounted lifetime utility over a period of 30 years.[43] The choice of the time span matters for the magnitude of the welfare but does not qualitatively affect the comparison across the policy scenarios.

There are several key findings. First, driving restrictions reduce consumer welfare especially for the high-income group despite the reduction in traffic congestion in both Tables 6 and 7.[44] There are two channels of impact as illustrated in Figure 1. On the one hand, the policy should reduce the deadweight loss from congestion relief. On the other hand, the policy leads to loss in consumer surplus by removing the choice of driving from the choice set in one out of five work days (equivalent to shifting the driving demand curve downward). The result suggests that the second channel dominates. The welfare loss is larger for high-income households because driving has a higher share among them. By reducing traffic speed, sorting exacerbates the welfare loss by 1% and 2% for high- and low-income groups, respectively.

Second, in contrast with driving restriction, congestion pricing disproportionally affect low-income households more in mode choices and consumer surplus given that these households are more price-sensitive. This distributional concern could hinder the political acceptability of congestion pricing and explain the limited adoption of congestion pricing despite it being continuously advocated by economists and urban planners. With the cycling of the congestion revenue, congestion pricing leads to a welfare gain for both income groups. In theory, the relative impact on consumer surplus and net welfare needs not to be the same, but the revenue recycling could be structured in a way to generate the same welfare outcome between the two groups. In our case, although the revenue from congestion pricing mostly comes from high-income households, we recycle it uniformly across income groups to achieve the same welfare gain for both groups. In fact, if the recycling is based on the source of revenue, high-income households would be better off under the policy while low-income household would be worse off. While the driving restriction disproportionally affects high-income households, congestion pricing could do the opposite without uniform revenue recycling to counteract it. This highlights the role that revenue from congestion pricing can play in addressing equity concerns. Sort-

[43] Our parameter estimates suggest a much larger marginal utility of housing price than the marginal utility of (per-trip) travel costs. On average, a 30-year housing tenure would imply 467 trips per year for male borrower ad 577 trips for female borrower. The implied trip numbers are plausible.

[44] The average household income in Beijing is about ¥167k in 2014. The average is ¥204k and ¥110k for high- and low-income groups, respectively.

ing strengthens congestion reduction and enhances welfare gain from congestion pricing, consistent with the finding in Langer and Winston (2008) based on a cross-section analysis for 98 US cities.

Figure 10 shows the welfare gain from different levels of congestion pricing under different assumptions. The optimal congestion price is 1.6 ¥/km and 1.4 ¥/km under 2008 and 2014 subway network, respectively. At the optimal levels of congestion pricing, sorting would increase consumer welfare by 60-70%, and supply adjustment contributes to another 10%-20%. The additional gain of sorting and supply side adjustment both stems from the reduced deadweight loss from congestion externality due to the further increase in traffic speed. This result highlights another reason for incorporating sorting to understand the impacts and cost-effectiveness of different transportation policies. Sorting also shifts the optimal congestion pricing level to the right, achieving higher level of equilibrium traffic speed. The figure also shows that under a wide range of levels of congestion pricing (<¥2.5/km) and different sorting assumptions, consumer welfare are always positive. This indicates that congestion pricing is likely to be an effective tool even when governments cannot gauge the exact pricing level a priori.

In our simulation table, we assume away the implementation cost of congestion pricing system in Beijing because the congestion pricing has yet to be implemented so we are not able to observe it. Singapore government provides a back of envelope calculation on the congestion toll system. It costs the government around 400 million dollars to install a satellite based road pricing system, which is likely to be what is required for Beijing to adopt the same policy. This translate into around 1,000 RMB per household, likely to be negligible in our welfare analysis (Under optimal pricing, one-year operation will create 4,000 RMB toll revenue per household, already enough to cover the cost).

Third, although subway expansion from 2008 to 2014 does not achieve the same level of congestion reduction as driving restriction and congestion pricing, it leads to a larger increase in consumer surplus, especially for the high-income group with and without sorting. The large increase in consumer surplus is consistent with the fact that the share of subway trips increases more than half after the expansion. Sorting slightly reduce the aggregate welfare gain due to the reduction in traffic speed. To gauge the magnitude of net consumer surplus, we calculate the construction cost and the operating cost during a 30-year period. Assuming that the cost are financed through a uniform lump-sum tax across households, consumer surplus for high-income households exceeds their tax burden, while consumer surplus of low-income households exceeds their tax burden without sorting, and marginally get hurt with sorting.

Fourth, the combination of congestion pricing and subway expansion achieves the largest congestion reduction and has the potential to achieve the largest welfare gain across five policy scenarios. The results in Column (6) also show that the revenue from congestion pricing could fully cover the costs of subway expansion. Earlier studies have shown that the revenue from optimal road pricing could be used to fully finance the capital and operating costs of transportation infrastructure under the condition that capacity and (pavement) durability costs are jointly characterized by constant returns to scale (Mohring and Harwitz, 1962; Winston, 1991; Verhoef and Mohring, 2009). In our simulation the cost of subway construction can indeed be covered by congestion pricing. The comparison highlights the advantage of congestion pricing from congestion reduction, welfare, and fiscal perspectives.

7 Conclusion

Transportation plays a critical role in determining residential locations, while at the same time, the pattern of residential locations affects the efficiency of the transportation system and policies. This study provides, to our knowledge, the first unified equilibrium sorting framework with endogenous congestion to empirically evaluate the efficiency and equity impacts of various transportation policies taking into account the interaction between the transportation system and the housing market. Our empirical analysis leverages spatially disaggregate data on travel behavior and housing transactions with information on residential and job locations in Beijing from 2006 to 2014. We first estimate a flexible travel mode choice model and then construct measures of ease-of-commuting for different properties. This house-job pair specific measure is determined by traffic congestion and transportation infrastructure, and enters the housing demand model as an observed housing attribute. Based on the estimates of model parameters, we conduct counterfactual simulations to examine the impacts and welfare consequences of various transportation policies from both the demand- and supply- sides: a driving restriction, congestion pricing, subway expansion, and combinations of demand-side and supply-side policies.

The parameter estimates from the flexible travel mode choice model imply the median value of time being two thirds of the hourly wage. The estimates from housing demand illustrate the importance of incorporating work commute in the model: doing so improves the model fit dramatically and affects preference estimates on other housing attributes. An average households is willing to pay 20% more in exchange for an easier work commute for the female member than for an equivalent improvement for the male member. The optimal congestion pricing taking into account sorting and supply-side responses is estimated to be ¥1.6/km and 1.4/km under 2008 and 2014 subway networks, respectively. Allowing for equilibrium sorting could have significant implications on welfare estimates of urban transportation policies: sorting accounts for over 60% of the welfare gain from optimal congestion pricing.

While different policies can be designed to attain the same level of congestion reduction, they lead to different spatial patterns of residential location. A driving restriction leads to an income-stratified structure that favors high-income households with respect to access to subways and jobs, which could disadvantage low-income households in the long run. Congestion pricing incentivizes residents to live closer to their job locations and the equilibrium sorting leads to a more compact city with shorter commutes to work for both income groups. Subway expansion does the opposite by increasing the separation of residence and workplace.

In addition to residential locations, different policies generate drastically different efficiency and equity consequences. While the driving restriction reduces social welfare due to the large distortion in travel choices, congestion pricing is welfare improving for both income groups with a uniform recycling of congestion revenue. A driving restriction generates a larger welfare loss among high-income households, while congestion pricing hurts low-income households more in the absence of revenue recycling, pointing to the underlying difference in political acceptability between the two policies. These results underscore both the distributional concern and the efficiency gain from congestion pricing relative to the driving restriction. The combination of congestion pricing and subway expansion stands out as the best policy among all policy scenarios from congestion reduction, social welfare, and fiscal perspectives. With the congestion pricing of ¥1.2/km and the observed subway expansion from 2008 to 2014, the policy mix generates the largest improvement in both traffic speed (about 25%) and welfare (¥43,000 per household). In addition, it is self-financing in that the revenue from congestion pricing could fully cover the cost of the subway expansion.

Our analysis does not consider the potential impacts of policies on intercity migration and the labor market. Both could be additional margins of adjustments that affect traffic congestion and urban spatial structure. Future research could relax these assumptions to capture even broader general equilibrium effects. Incorporating these channels in our current framework with rich heterogeneity and endogenous congestion would necessitate additional data and computational resources. Nevertheless, such a framework would allow the existence of both congestion and agglomeration forces, which could affect the nature of the interaction between transportation policies and urban spatial structure.

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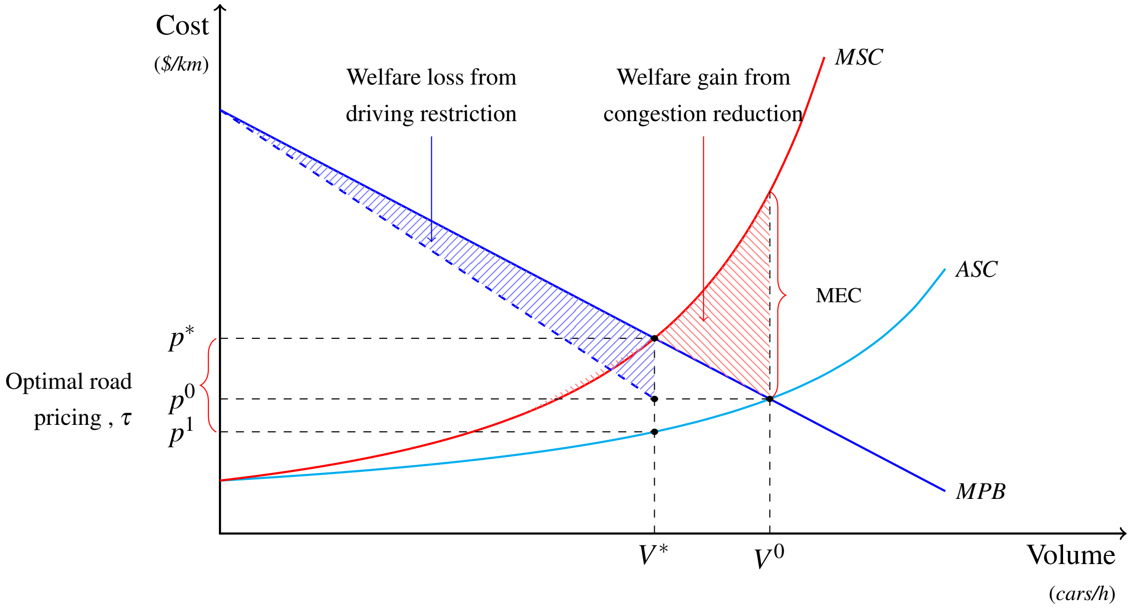
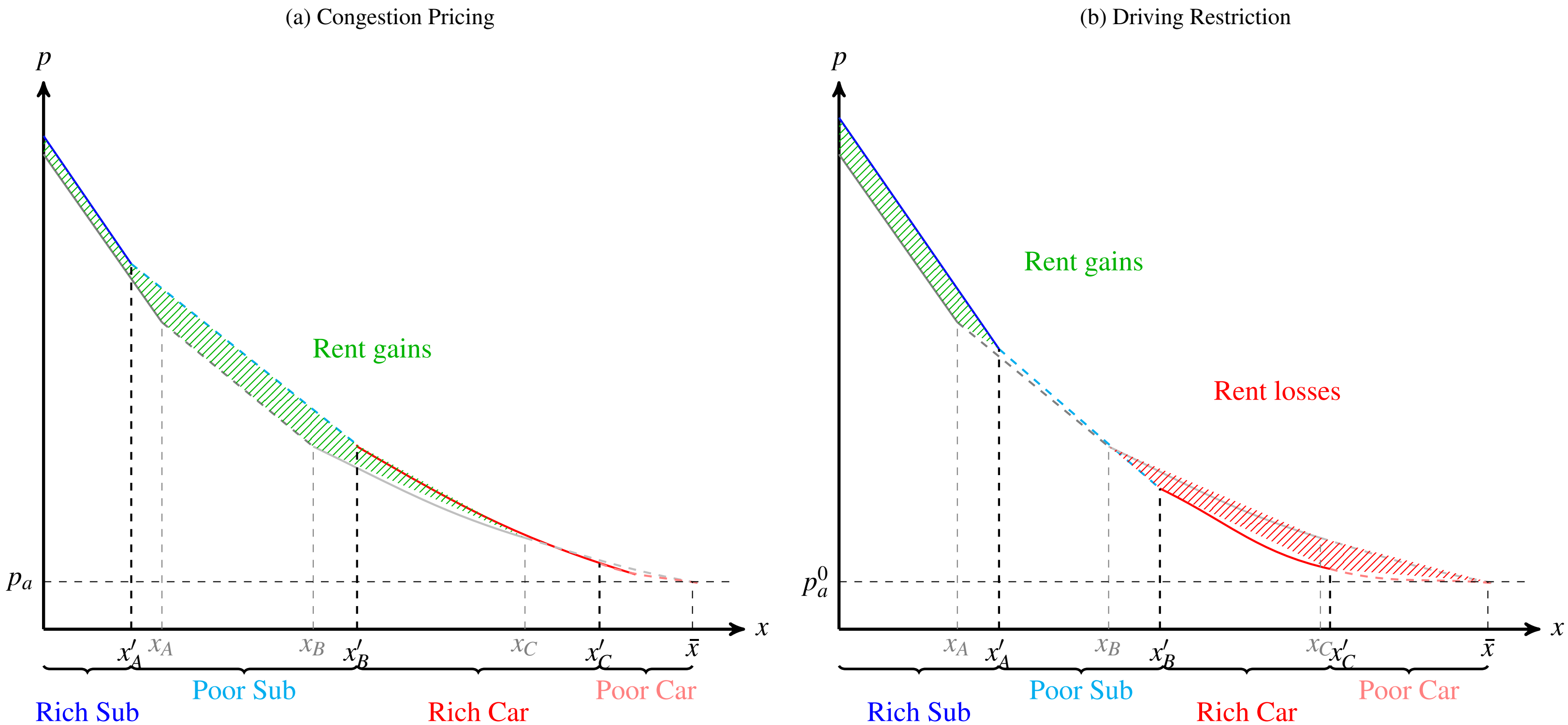
Figure 1: Traffic under Congestion Pricing and Driving Restriction



Note: The figure illustrates the welfare impacts of optimal congestion pricing and driving restriction. The x-axis denotes traffic volume (or throughput measured in the number of cars per hour passing the point). The marginal private benefit *MPB* curve represents the demand curve for driving (willingness to pay for driving). The average social cost *ASC* curve reflects the private cost of driving, which is experienced based upon the average time cost across the vehicles on the road. The difference between *ASC* and the marginal social cost, *MSC*, is the congestion externality (or the marginal external cost of congestion, *MEC*). In the absence of any intervention, equilibrium occurs at V^0 compared to the social optimal level of traffic volume is V^*. The shaded area on the right (red area) shows the deadweight loss due to excess congestion. A Pigouvian tax, τ, can be imposed to achieve the optimal level V^*. Alternatively, a driving restriction can be adopted to achieve the same level of congestion reduction but it would incur a welfare loss denoted by the shaded area on the left (blue area) assuming that the reduction of trips is random among all privately beneficially trips. Therefore, the welfare impact of the driving restriction is ambiguous *a priori*.

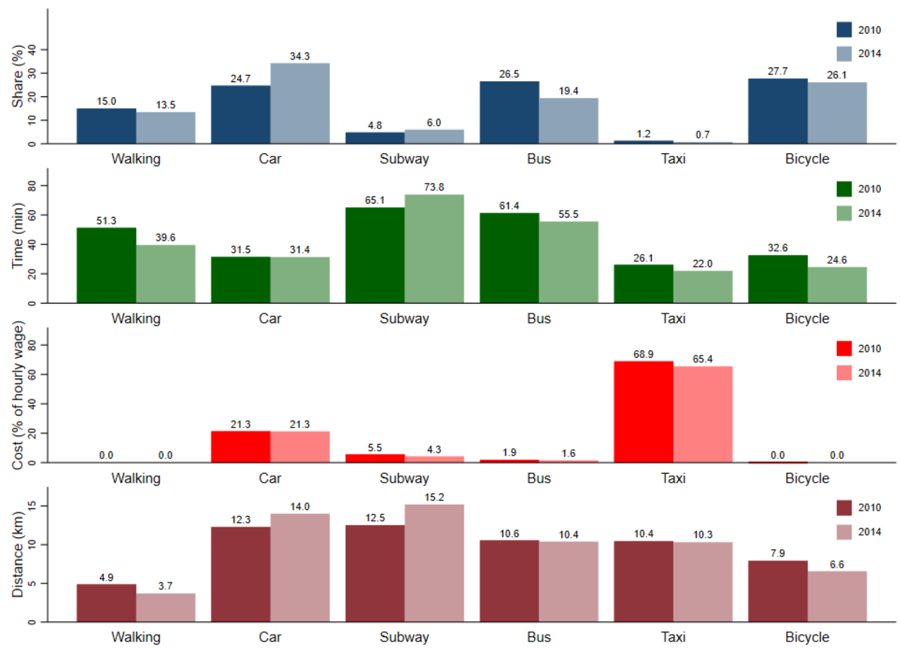
Figure 2: Welfare Effects of Transportation Policies with Sorting



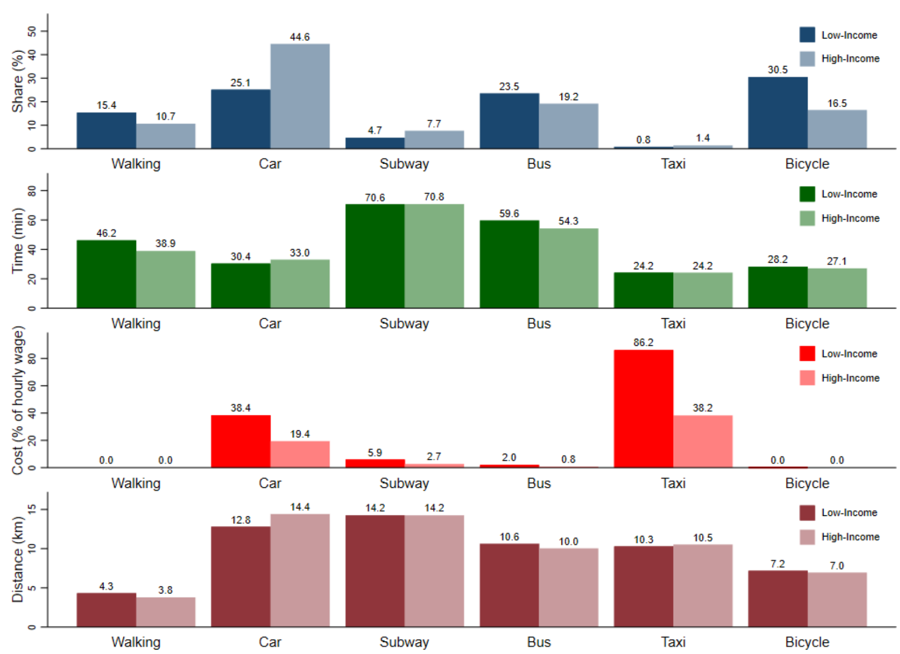
Note: This figure illustrates the capitalization of commuting cost changes into the housing market with sorting. A full exposition of the individual bid-rent curves in the diagram is provided in the Appendix as well as the underlying assumptions and equilibrium conditions. The left panel shows the effect of a distance-based congestion charge. Colored lines refer to the equilibrium bid rent functions lying along the envelope corresponding to rich subway, poor subway, rich driving, poor driving moving from the CBD to the urban boundary. Grey lines correspond to the no-policy baseline bid-rent envelope. The boundaries marked with a prime indicate the change in spatial structure induced by sorting, namely that fewer rich and more poor take the subway. The area between the policy and no-policy bid-rent envelopes reflects the capitalization effect of transportation policies, which corresponds to net welfare improvement. Congestion pricing induces a welfare increase for subway commuters, based largely on the effect of recycled revenues. It also induces a improvement in welfare for rich drivers reflecting the impact of lower congestion net of the cost of the congestion fee. It also induces an almost negligible decrease in welfare for poor drivers reflecting their smaller values of time. In contrast, the driving restriction in the right panel shows how the rich are induced to increase subway commuting and the poor do, albeit by a trivial amount. The driving restriction induces a gain for subway commuters, but a larger loss for those driving because of the time costs associated with using subway on long commuters during restricted days.

Figure 3: Travel Patterns for Commuting Trips from Beijing Household Travel Survey

(a) 2010 vs. 2014



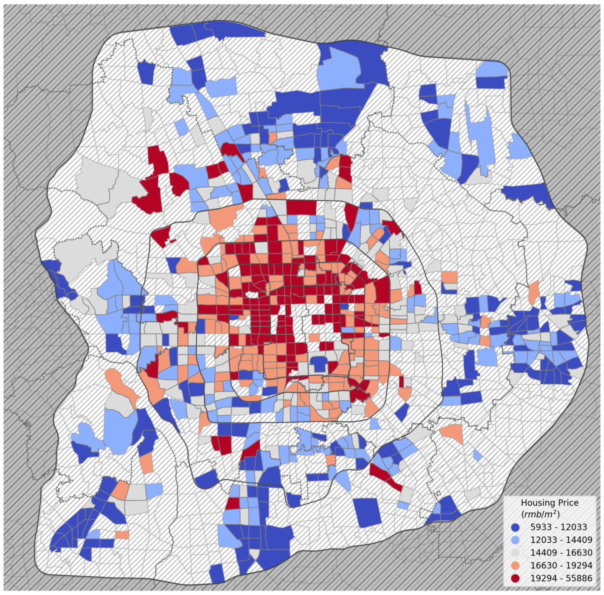
(b) High income vs. Low Income



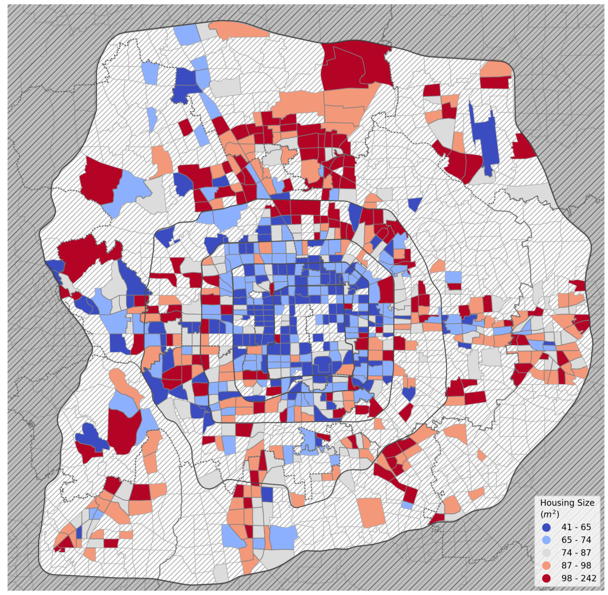
Note: This figure plots trip share, time, and costs by different modes for work commuting trips in the Beijing Household Travel Survey of 2010 and 2014. The mode shares are based on chosen modes in the data. Travel time, cost, and distance are constructed and are shown for the corresponding chosen modes. High-income households are defined as households whose income level is greater than the median in the survey year.

Figure 4: Housing and Household Attributes from Housing Mortgage Data

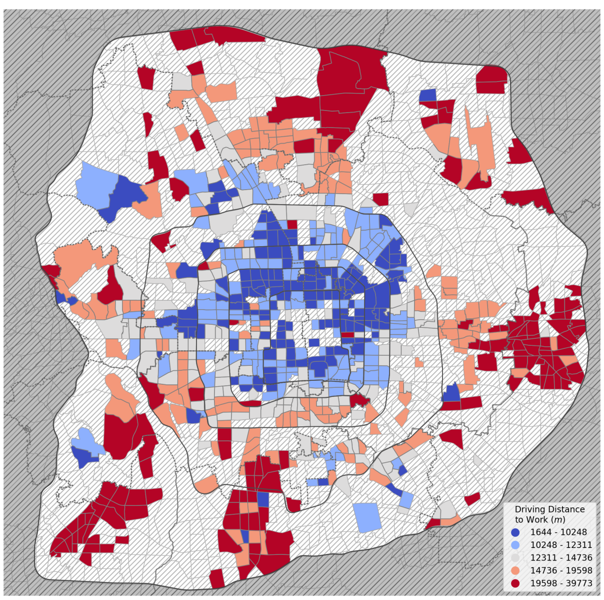
(a) Housing Price (¥/m^2)



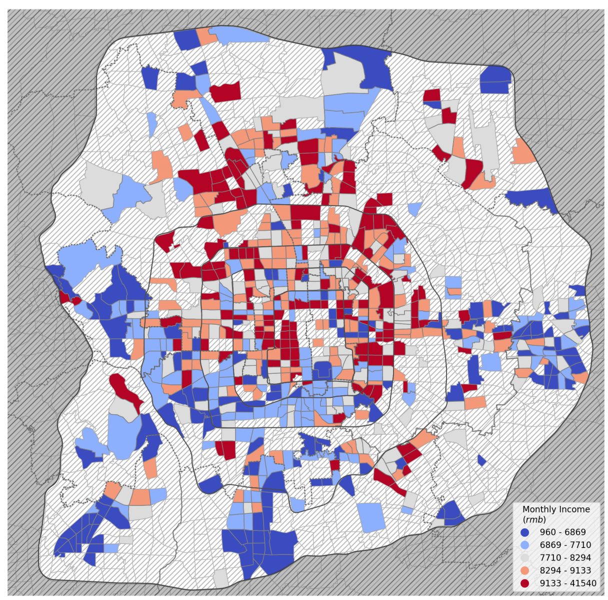
(b) Housing Size (m^2)



(c) Distance to Work (m)

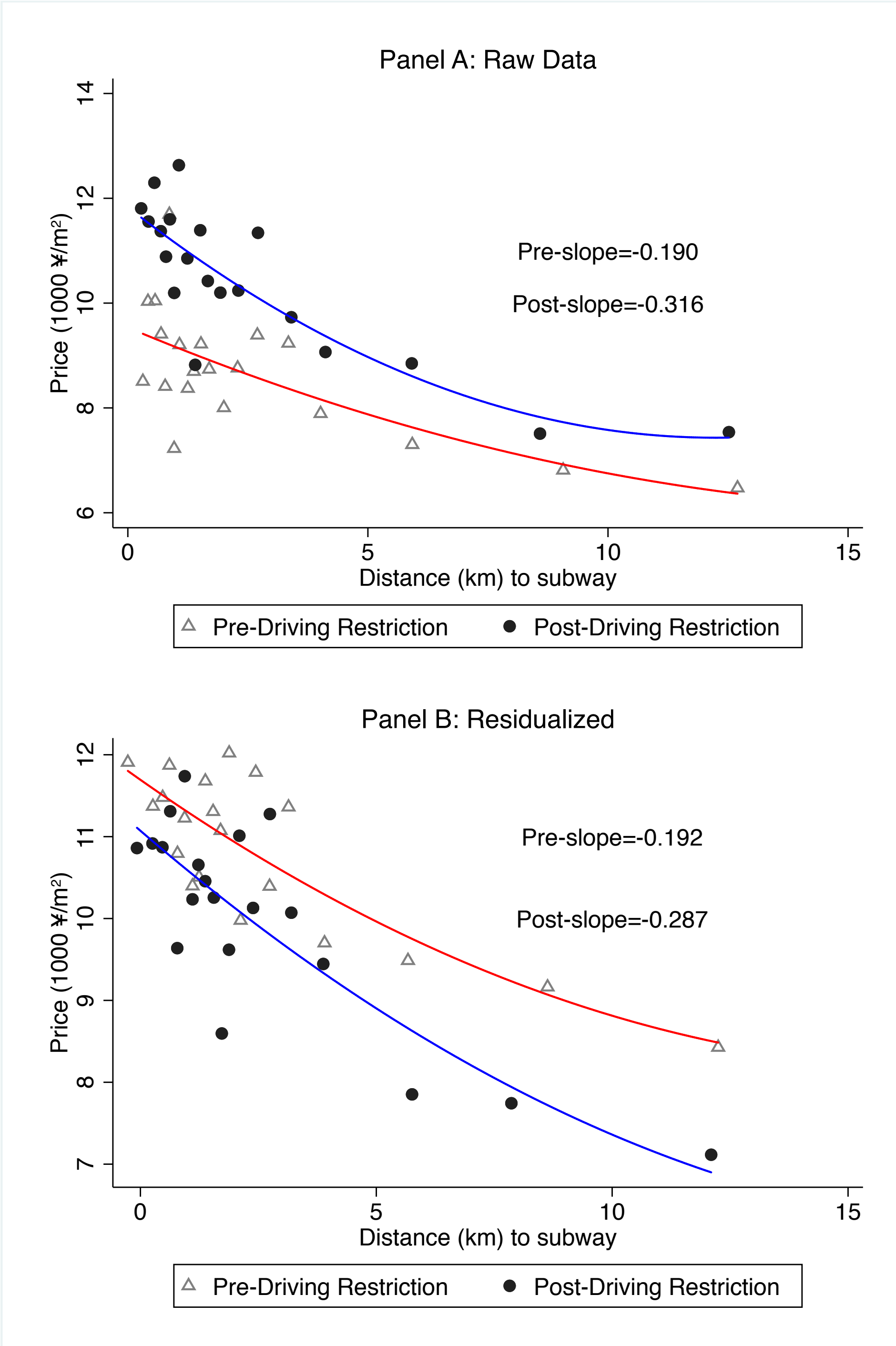


(d) Monthly Household Income (¥)



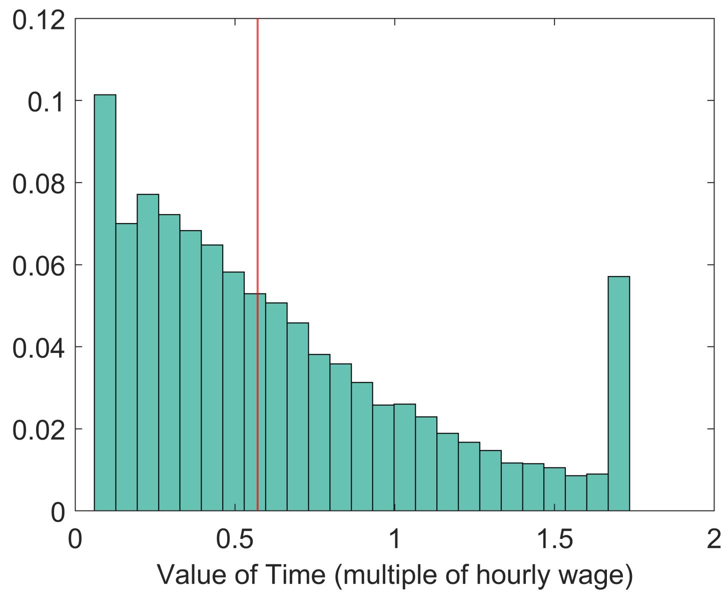
Note: This figure plots the averages of key housing and household attributes by Traffic Analysis Zone (TAZ) based on mortgage data from 2006 to 2014. The values are the averages across properties in the TAZ from the mortgage data during the data period. Distance to work is the driving distance to work for all borrowers in the data (including primary and secondary borrowers when both are present). Monthly household income is based on the income of the households at the time of purchase in the given TAZ. Values are classified into five quintiles: the red color corresponds to larger values while the blue color for low values. The white color represents no observations in the TAZ.

Figure 5: Reduced Form Evidence: Housing Price Gradient before and after Driving Restriction



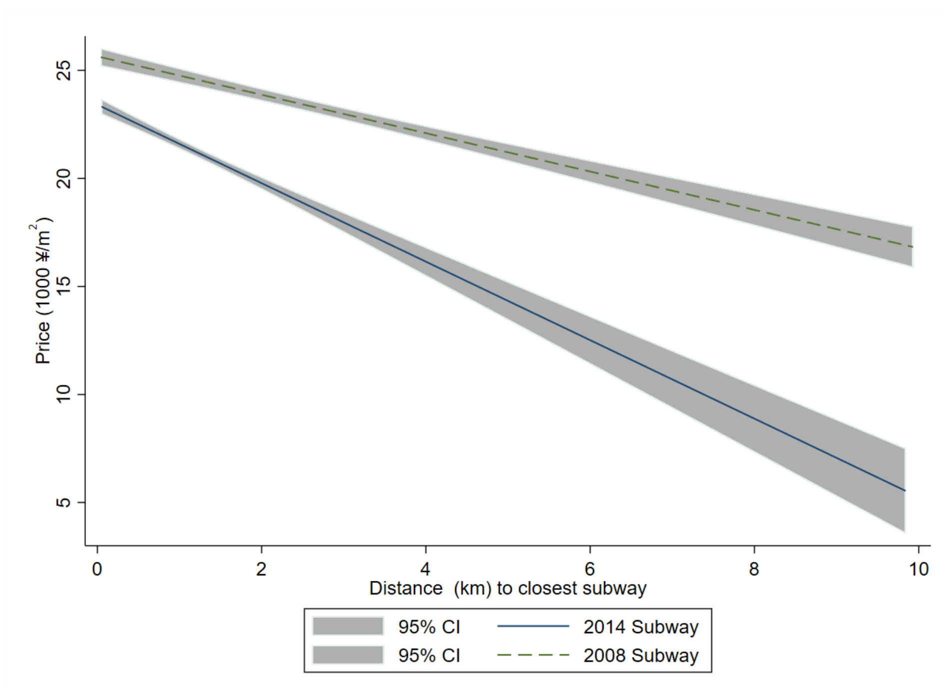
Notes: These binned scatterplots show housing price per square meter against distance to subway before and after the driving restriction goes into effect in Beijing. The sample spans 24 months before and after the policy starting point (July 2008). The top panel is the binned scatter plot based on the raw data of price per m^2 and the distance to the nearest subway station. The bottom panel controls for neighborhood fixed effects, and year by month fixed effects. The slopes denoted on the figure are based on quadratic fits.

Figure 6: Implied Value of Time Distribution from Mode Choice Estimation



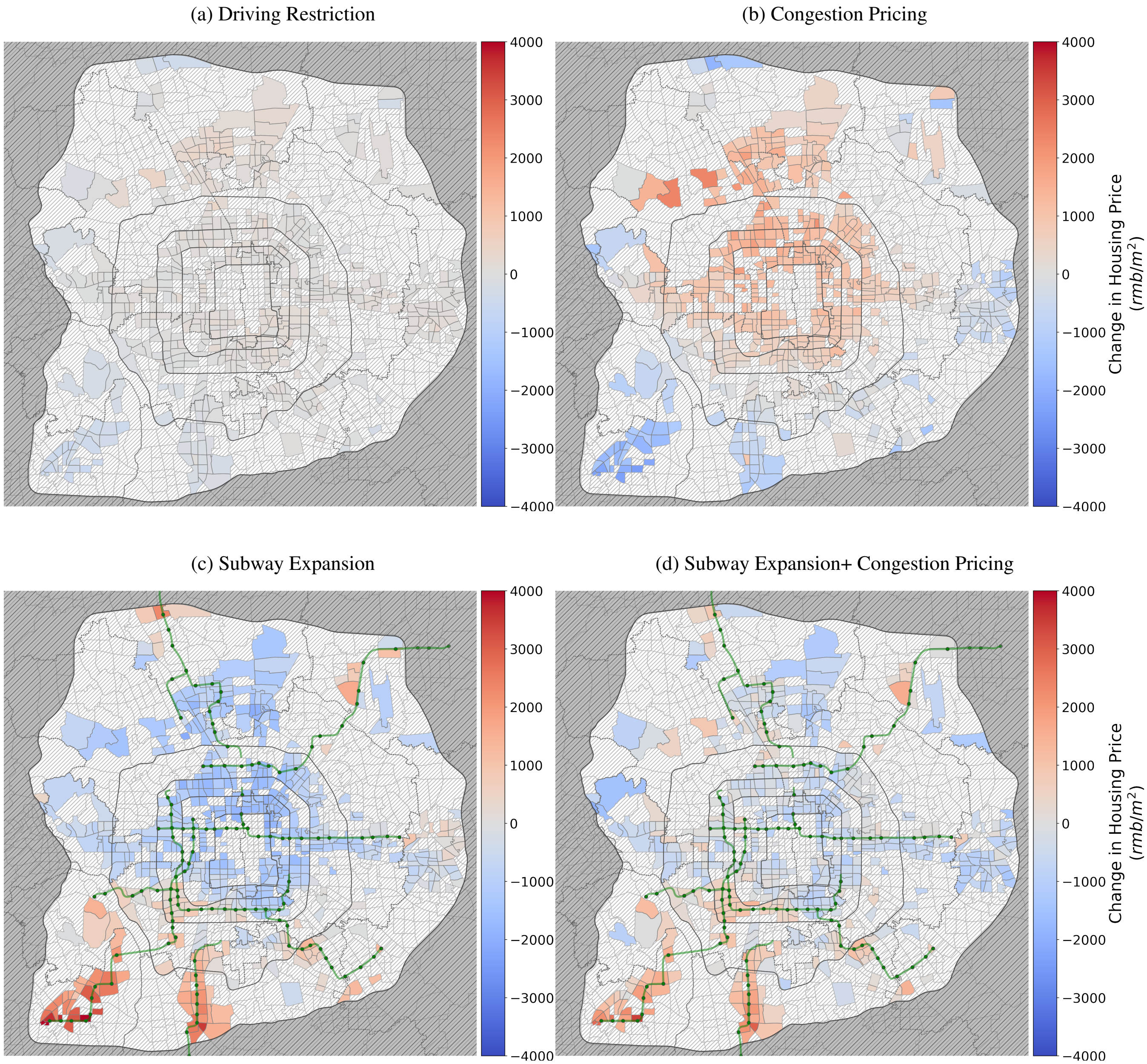
Note: The figure plots the distribution of the implied value of time (VOT) is based on the last specification of our mode choice model in Table 3. The preference on travel time has a winsorized (at 95th and 5th percentile) chi-square distribution with degrees of freedom equal to three while the preference on travel cost is inversely proportional to income. The value of time is in terms of hourly wage. The red line shows the mean VOT (75.6% of hourly wage). The median VOT is 68% of hourly wage.

Figure 7: Price Gradient under 2008 and 2014 Subway Networks



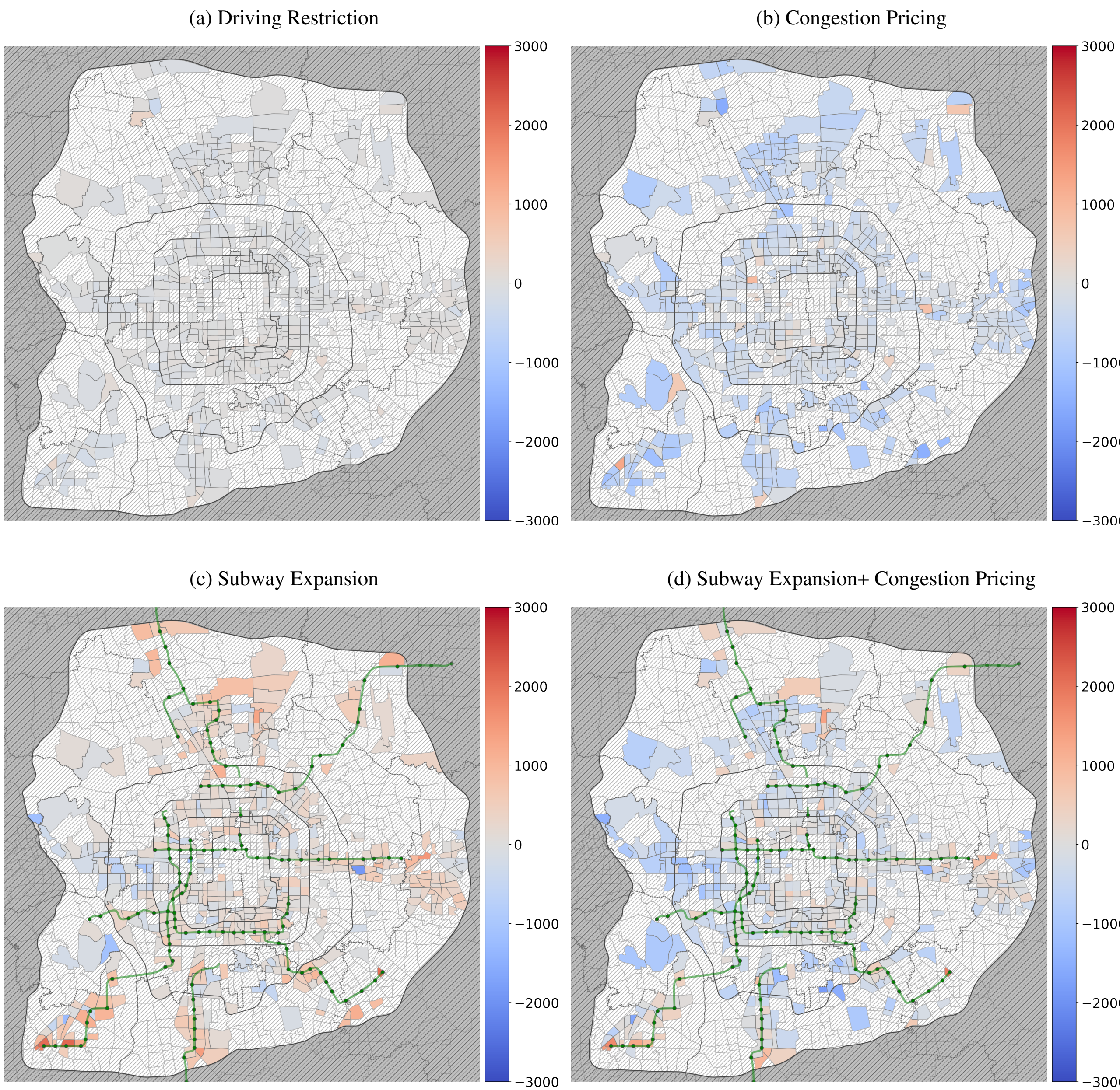
Note: The plot shows the price gradient with respect to subway distance under the 2008 and 2014 networks, respectively.

Figure 8: Changes in Housing Prices from Simulated Policies (¥$/m^2$)



Note: This figure illustrates changes in property prices under different policy scenarios (relative to the baseline scenario of no policy) based on the simulations in Table 7. Each cell represents a TAZ. Redder colors corresponds to an increase in price while a cold color represents a decrease. Cells in white have no observations in the simulation sample period in the TAZ. Green lines represent new subway lines from year 2008 to 2014.

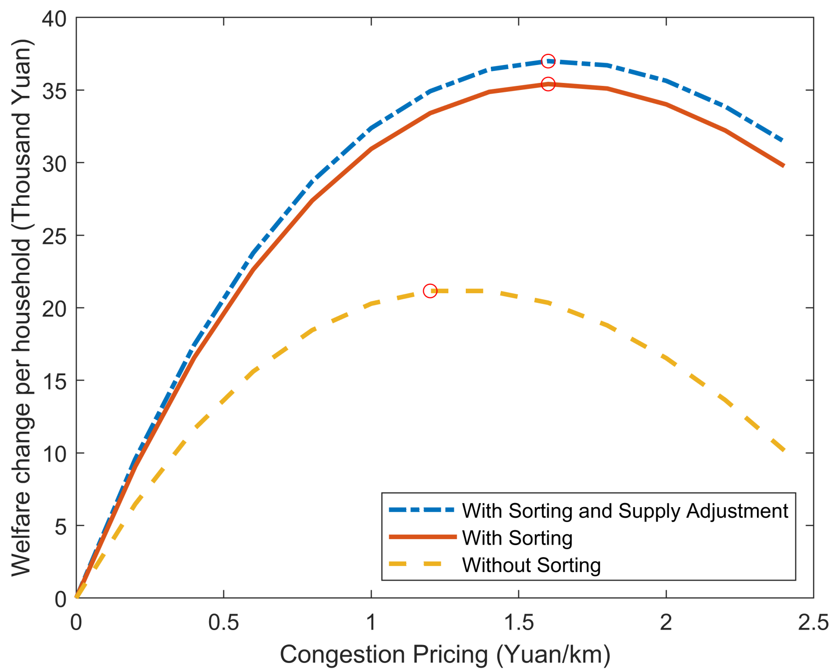
Figure 9: Changes in Commuting Distance from Simulated Policies (in meters)



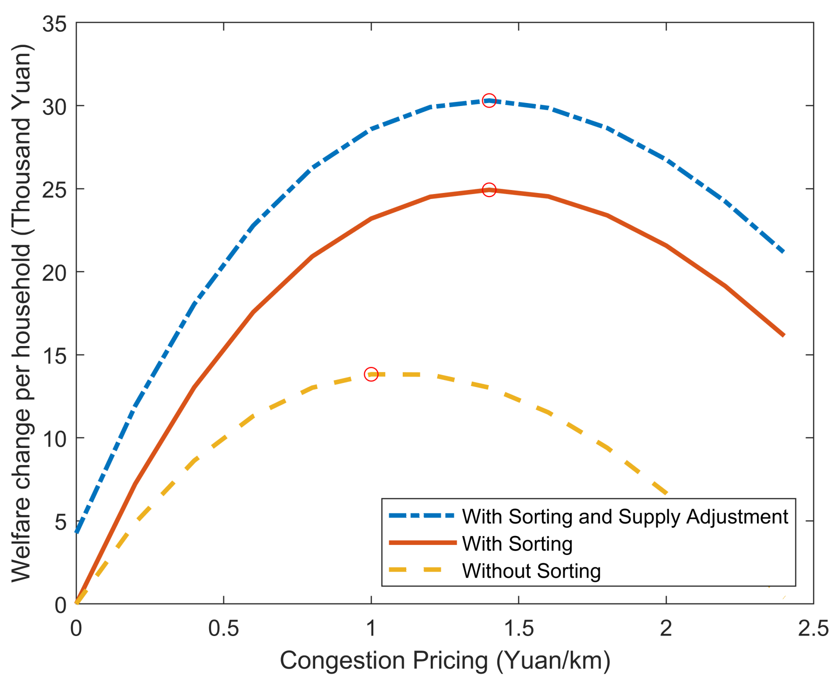
Note: This figure illustrates changes in commuting distance under different policy scenarios (relative to the baseline scenario of no policy) based on the simulations in Table 7. Each cell represents a TAZ. A warm color corresponds to an increase in distance while a cold color represents a decrease. Cells in white have no observations in the simulation sample period in the TAZ. Green lines represent new subway lines from year 2008 to 2014.

Figure 10: Optimal Congestion Pricing under 2008/2014 Subway Networks

(a) 2008 Subway Network



(b) 2014 Subway Network



Note: The plot shows the welfare change with respect to congestion pricing under 2008/2014 subway networks, without sorting (PE scenario, yellow dotted line), with sorting (GE scenario, orange solid line), or with sorting and supply adjustment (blue dashed line). Without sorting, the optimal congestion pricing is ¥1.2/km for 2008 subway system and ¥1/km for 2014. Sorting shifts the optimal toll to the right. The optimal congestion pricing is ¥1.6/km for 2008 subway system and ¥1.4/km for 2014 under sorting. The difference of "with sorting" and "without sorting" welfare shows the welfare gain from household sorting. The difference of "with sorting" and "without sorting and supply adjustment" welfare shows the welfare gain from supply adjustment.

Table 1: Summary Statistics of Household Travel Survey

	2010			2014		
	N	Mean	SD	N	Mean	SD
Respondent characteristics						
Income: <50k	14780	0.48	0.50	20573	0.18	0.38
Income: [50k, 100k)	14780	0.39	0.49	20573	0.44	0.50
Income: >=100k	14780	0.13	0.34	20573	0.38	0.49
Having a car (=1)	14780	0.44	0.50	20573	0.62	0.49
Female (=1)	14780	0.44	0.50	20573	0.43	0.50
Age (years)	14780	37.59	10.28	20573	38.47	9.84
College or higher (=1)	14780	0.61	0.49	20573	0.64	0.48
Home within 4th ring (=1)	14780	0.51	0.50	20573	0.41	0.49
Workplace within 4th ring (=1)	14780	0.59	0.49	20573	0.50	0.50
Trip related variables						
Travel time	30334	0.87	1.06	42820	0.74	0.98
Travel cost	30334	2.47	5.55	42820	3.83	6.96
Distance<2km	30334	0.25	0.43	42820	0.24	0.43
Distance within 2-5km	30334	0.27	0.45	42820	0.26	0.44
Walk	30334	0.17	0.37	42820	0.15	0.35
Bike	30334	0.27	0.45	42820	0.26	0.44
Bus	30334	0.26	0.44	42820	0.19	0.39
Subway	30334	0.05	0.21	42820	0.06	0.24
Car	30334	0.24	0.43	42820	0.34	0.47
Taxi	30334	0.01	0.11	42820	0.01	0.09

Note: The table reports respondent and trip characteristics of all commuting trips within the 6th ring road from 2010 and 2014 Beijing Household Travel Survey, which account for 50% of all trips in the survey. The number of observed respondents is 14,780 and 20,573. On average, each respondent reports 2.1 commuting trips in the survey. Travel time and travel cost variables are those associated with the chosen modes, and are constructed by the authors as shown in Appendix B.2. Distance<2km and Distance within 2-5km denotes straight-line distance and captures short to medium-distance commuting trips. There are six main trip modes: walk, bike, bus, subway, car, and taxi. For bus and subway trips, they could include segments with other modes but we characterize them as the bus and subway trips. Trips using both bus and subway are rare less than XXX% in the data and we drop them in the analysis.

Table 2: Summary Statistics of Housing Data

	Mean	SD	Min	Max
Property attributes				
Transaction year	2011	1.89	2006	2014
Price/m^2 (¥'000s)	19.83	9.56	5.00	68.18
Unit size (m^2)	92.68	40.13	16.71	400.04
Household annual income (¥'000s)	159.71	103.34	6.24	2556.90
Primary borrower age	33.99	6.62	20.00	62.00
Housing complex attributes				
Distance to key school (km)	6.05	5.61	0.03	23.59
Complex vintage	2004	8	1952	2017
Green space ratio	0.32	0.06	0.03	0.85
Floor to land area ratio	2.56	1.12	0.14	16.00
No. of units	1972	1521	24	13031
Home-work travel variables				
Walking distance (km)	14.10	9.51	0.00	62.92
Driving distance (km)	16.13	10.87	0.00	85.22
Home to subway distance (km)	2.13	2.31	0.04	28.37
Subway route distance (km)	15.17	10.70	0.00	68.40

Note: This table reports statistics from the mortage dataset over 2006-2014. The number of housing transactions is 79,884, all of which are within the 6th ring road. The dataset is weighted to match the statistics of real-estate listings. Housing complex is defined as a group of building in the same development. Distance to key school is the distance of home to the nearest elementary school with a key school designation. Distance to park is the distance to the nearest park or green space. Home-work travel variables are constructed following the same method as outlined in the household travel survey. Home to subway distance is the distance from home to the nearest subway station. Subway route distance is the distance between the two subway stations that are closest to home and work locations.

Table 3: Estimation Results of Travel Mode Choices

	Logit			Random Coefficient		
	(1)	(2)	(3)	(4)	(5)	(6)
Travel Time (γ_1)	-0.623	-0.489	-0.345			
	(0.013)	(0.011)	(0.012)			
Travel Cost/Hourly Wage (γ_2)	-0.438	-1.549	-0.721	-1.260	-9.763	-9.321
	(0.047)	(0.065)	(0.080)	(0.084)	(0.291)	(0.286)
Random coefficients on travel time (μ_γ)						
Travel Time				-2.690	-2.837	-2.701
				(0.016)	(0.058)	(0.058)
Random coefficients on mode-specific constants (σ_m)						
Driving					25.223	21.681
					(0.485)	(0.425)
Subway					17.280	18.988
					(0.426)	(0.477)
Bus					25.395	28.177
					(0.791)	(0.915)
Bike					57.913	55.327
					(1.641)	(1.598)
Taxi						13.683
						(0.502)
Mode*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mode*Trip related FE		Yes	Yes	Yes	Yes	Yes
Mode*Demographic FE			Yes	Yes	Yes	Yes
Log-likelihood	-62477	-59255	-47622	-40960	-26468	-26450
Implied mean VOT	1.422	0.316	0.479	5.574	0.758	0.756
Implied median VOT	1.422	0.316	0.479	4.989	0.679	0.677

Note: The number of observations are 73,154. All six specifications include a rich set of fixed effects interacting with mode-specific constants (travel model dummies). Trip related FE includes trip distance bins and the origin and destination dummies (e.g., if the origin is within 2nd ring row). Demographics FE includes respondent's age, gender, education, and car ownership. The first three specifications are multinomial logit while the last three add random coefficients to the model. 200 randomized Halton draws are used to estimate the random coefficients in the last three specifications. The distribution of the preference on time in the last three specifications is specified as a chi-square distribution (truncated at 5th and 95th percentile) with degrees of freedom equals three: $\mu_\gamma \chi^2(3)$ so as to capture the long tail of VOT distribution. The estimates of μ_γ are provided in the table. The random coefficients on travel mode dummies (driving, subway, bus, bike, and taxi) are assumed to have normal distribution (walking is taken as the baseline group). The estimates of σ of those normal distributions are provided in the table. The last row provides the implied median value of time for each specification. Standard errors clustered at the respondent level are below estimates: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Estimation Results of Housing Choices - Nonlinear Parameters

	No EV		No Random Coef.		Random Coef.	
	Para	SE	Para	SE	Para	SE
Demographic Interactions						
Price (in 1 million RMB)*ln(income)	0.965	0.007	0.998	0.008	1.031	0.008
Age in 30-45*ln(distance to key school)	-0.329	0.004	-0.411	0.005	-0.446	0.006
Age $>$ 45*ln(distance to key school)	-0.074	0.009	-0.176	0.010	-0.186	0.011
Age in 30-45*ln(property size)	1.343	0.014	1.452	0.015	1.501	0.016
Age $>$ 45*ln(property size)	2.394	0.028	2.647	0.031	2.739	0.033
EV_{Male}			0.271	0.010	0.294	0.012
EV_{Female}			0.332	0.011	0.363	0.013
Random Coefficients						
$\sigma(EV_{Male})$					0.158	-0.025
$\sigma(EV_{Female})$					0.209	-0.024
Log-likelihood	-723900		-593370		-590829.3	

Note: The estimation uses weighted mortgage plan data from Year 2008-2014. The number of observations is 79,884. The results are from MLE. The first specification does not include EV (the matching value of home-work commute); the second specification does; the third specification further controls random coefficients on EV terms. EV is constructed using by taking observed household demographics into travel model estimates (Column 6 of Table 3). The big decrease in log-likelihood from the first to the second specification indicates strong explanatory power of EV term.

Table 5: Estimation Results of Housing Choices - Linear Parameters

	OLS	OLS	IV1	IV1+IV2	IV3	All
	(1)	(2)	(3)	(4)	(5)	(6)
Price (million RMB)	-2.240***	-2.190***	-6.585***	-6.554***	-7.143***	-6.700***
	(0.187)	(0.184)	(0.920)	(0.594)	(1.654)	(0.545)
Ln(property size)	-3.662***	-3.810***	3.846**	3.793***	4.799	4.047***
	(0.259)	(0.264)	(1.595)	(1.042)	(2.952)	(0.988)
Building age	-0.044***	-0.030***	-0.132***	-0.132***	-0.146***	-0.135***
	(0.007)	(0.006)	(0.021)	(0.014)	(0.040)	(0.013)
Floor to Area Ratio	-0.006	-0.009	-0.023	-0.023	-0.019	-0.023
	(0.034)	(0.026)	(0.033)	(0.033)	(0.036)	(0.034)
Ln(dist. to park)	0.214***	0.073	-0.424***	-0.420***	-0.481**	-0.436***
	(0.070)	(0.058)	(0.124)	(0.103)	(0.224)	(0.105)
Ln(dist. to key school)	0.988***	0.817***	0.323**	0.327***	0.238	0.311**
	(0.082)	(0.140)	(0.148)	(0.124)	(0.214)	(0.121)
Year-Month-District FE	Y	Y	Y	Y	Y	Y
Neighborhood FE		Y	Y	Y	Y	Y
First-stage F			10.48	14.22	9.88	14.22
Avg. Price elasticity	2.761	2.811	-1.579	-1.549	-2.129	-1.699

Note: The number of observations is 79,884. The dependent variable is the mean utilities recovered from the first stage. The first two columns are from OLS and the last four are from IVs. Complex density is measured by the floor-area ratio of the complex, the size of the total floor area over the size of the parcel that the complex is located on. Distance to key school is the distance to the nearest key elementary school. Column (3) and (4) use IV1 as price instruments, i.e. the average attributes of properties (building size, age, log distance to park, and log distance to key school) that are within 3km outside the same complex sold in a two-month time window from a given property. Column (4) and (6) additionally use IV2, i.e. the interaction between the distance related instruments defined in Column (3) and the winning odds of the vehicle licence lottery as instruments. The winning odds decreased from 9.4% in Jan. 2011 to 0.7% by the end of 2014. Column (5) uses number of houses transacted in the three-month time window in the real estate listings dataset. Standard errors clustered at the neighborhood-year level are in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Simulation Results: without Sorting

	2008 Subway Network						2014 Subway Network					
	(1) No Policy		(2) Driving restriction		(3) Congestion pricing		(4) No Policy		(5) Driving restriction		(6) Congestion pricing	
	Baseline levels		Δs from (1)		Δs from (1)		Δs from (1)		Δs from (1)		Δs from (1)	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Panel A: Travel outcomes												
Drive	40.87	23.79	-5.90	-3.33	-2.79	-4.45	-1.76	-1.43	-7.45	-4.63	-4.63	-5.48
Subway	10.24	13.49	1.13	0.59	1.03	1.08	4.52	5.51	5.97	6.24	5.85	6.53
Bus	22.73	29.45	2.15	1.33	0.61	1.61	-1.52	-2.25	0.44	-0.96	-0.86	-0.64
Bike	17.10	22.91	0.73	0.36	0.45	0.91	-0.52	-0.77	0.22	-0.39	-0.10	0.12
Taxi	1.80	0.86	0.81	0.29	0.42	0.25	-0.35	-0.31	0.28	-0.08	-0.07	-0.15
Walk	7.26	9.51	1.08	0.75	0.28	0.61	-0.37	-0.75	0.54	-0.19	-0.19	-0.37
Speed	20.69		3.54		3.24		1.70		5.10		4.80	
Panel B: Housing market outcomes												
Male's distance to work (km)	19.45	18.88										
Female's distance to work (km)	17.86	12.21										
Distance to subway (km)	5.77	4.67					-4.57	-3.82	-4.57	-3.82	-4.57	-3.82
Panel C: Welfare analysis per household (thousand ¥)												
Consumer surplus (+)			-238.0	-54.4	-144.1	-106.1	126.9	95.3	-111.1	40.4	-17.1	-5.8
Toll revenue (+)					146.7	146.7					136.3	136.3
Subway cost (–)							77.6	77.6	77.6	77.6	77.6	77.6
Net welfare			-238.0	-54.4	2.6	40.6	49.3	17.7	-188.7	-37.2	41.6	52.9

Note: Simulated results based on estimated model parameters in Column (6) of Table 3 and Column (6) of Table 5. The simulation shows counterfactual results for 2014 sample households and houses. The detailed simulation procedure can be found in E. This table shows results without sorting, hence households' housing choice decisions are fixed but we allow travel mode decisions to adjust to clear traffic market. Column (1) shows the baseline results while columns (2) to (6) show the differences from column (1). The driving restriction prohibits driving in one of five work days. Congestion pricing is ¥1.22 per km to generate the same reduction as the driving restriction without sorting in Table 7. High-income household are those with income above the median household income. Subway cost per household includes the construction cost and the 30-year operating cost equally shared among 7.2 million households. We apportion 75% it to work commute in our welfare analysis. Toll revenue is the revenue per household from congestion pricing during a 30-year period (to keep a balanced government budget, the toll revenue is recycled uniformly to each household). Net welfare is consumer welfare per household after revenue recycling or tax-funded subway construction and operation.

Table 7: Simulation Results: with Sorting

	2008 Subway Network						2014 Subway Network					
	(1) No Policy		(2) Driving restriction		(3) Congestion pricing		(4) No Policy		(5) Driving restriction		(6) Congestion pricing	
	Baseline levels		Δs from (1)		Δs from (1)		Δs from (1)		Δs from (1)		Δs from (1)	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Panel A: Travel outcomes												
Drive	40.87	23.79	-6.05	-3.50	-2.73	-4.38	-1.69	-1.57	-7.55	-4.71	-4.64	-5.54
Subway	10.24	13.49	1.18	0.62	0.99	0.99	3.84	5.03	6.22	6.50	5.88	6.66
Bus	22.73	29.45	2.16	1.40	0.52	1.57	-1.35	-2.01	0.44	-0.97	-0.89	-0.66
Bike	17.10	22.91	0.75	0.36	0.44	0.90	-0.44	-0.72	0.17	-0.43	-0.11	0.09
Taxi	1.80	0.86	0.79	0.28	0.43	0.25	-0.31	-0.29	0.24	-0.11	-0.08	-0.16
Walk	7.26	9.51	1.18	0.85	0.35	0.67	-0.05	-0.44	0.48	-0.27	-0.15	-0.39
Speed	20.69		3.52		3.52		1.44		4.82		4.89	
Panel B: Housing market outcomes												
Male's distance to work	19.45	18.88	0.02	0.03	-0.28	-0.11	0.17	0.21	0.22	0.23	-0.15	0.08
Female's distance to work (km)	17.86	12.21	0.01	0.03	-0.24	-0.07	0.23	0.25	0.27	0.27	-0.05	0.16
Distance to subway (km)	5.77	4.67	-0.03	0.03	-0.04	0.04	-4.57	-3.81	-4.57	-3.81	-4.57	-3.81
Panel C: Welfare analysis per household (thousand ¥)												
Consumer surplus (+)			-238.6	-55.5	-130.0	-91.3	120.7	75.0	-116.2	19.0	-12.4	-14.9
Toll revenue (+)					145.5	145.5					136.1	136.1
Subway cost (–)							77.6	77.6	77.6	77.6	77.6	77.6
Net welfare			-238.6	-55.5	15.5	54.2	43.1	-2.6	-193.8	-58.6	46.2	43.6

Note: Simulated results based on estimated model parameters in Column (6) of Table 3 and Column (6) of Table 5. The simulation shows counterfactual results for 2014 sample households and houses. The detailed simulation procedure can be found in E. This table shows results with sorting, hence we allow households' housing choice decisions and travel mode decisions to adjust to clear traffic market and housing market. Column (1) shows the baseline results while columns (2) to (6) shows the differences from column (1). Driving restriction prohibits driving in one of five work days. Congestion pricing is ¥1.22 per km to generate same reduction as driving restriction. High-income household are those with income above the median household income. Subway cost per household includes the construction cost and the 30-year operating cost equally shared among 7.2 million households. We apportion 75% it to work commute in our welfare analysis. Toll revenue is the revenue per household from congestion pricing during a 30-year period (to keep a balanced government budget, the toll revenue is recycled uniformly to each household). Net welfare is consumer welfare per household after revenue recycling or tax-funded subway construction and operation.

Table 8: Simulation Results: with Sorting and Supply Adjustment

	2008 Subway Network						2014 Subway Network					
	(1)		(2)		(3)		(4)		(5)		(6)	
	No Policy		Driving restriction		Congestion pricing		No Policy		Driving restriction		Congestion pricing	
	Baseline levels		Δs from (1)		Δs from (1)		Δs from (1)		Δs from (1)		Δs from (1)	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Panel A: Travel outcomes												
Drive	40.87	23.79	-5.93	-3.33	-2.72	-4.34	-1.95	-1.61	-7.61	-4.77	-4.67	-5.58
Subway	10.24	13.49	1.18	0.59	1.03	1.04	4.89	5.91	6.39	6.68	5.96	6.76
Bus	22.73	29.45	2.15	1.36	0.45	1.45	-1.50	-2.21	0.44	-0.94	-0.89	-0.64
Bike	17.10	22.91	0.72	0.36	0.43	0.87	-0.57	-0.83	0.15	-0.46	-0.13	0.07
Taxi	1.80	0.86	0.80	0.28	0.43	0.25	-0.41	-0.35	0.22	-0.12	-0.09	-0.17
Walk	7.26	9.51	1.08	0.74	0.38	0.72	-0.45	-0.91	0.42	-0.38	-0.17	-0.44
Speed	20.69		3.52		3.72		1.11		4.48		4.75	
Panel B: Housing market outcomes												
Male's distance to work (km)	19.45	18.88	0.03	0.04	-0.48	-0.29	0.51	0.53	0.60	0.59	0.01	0.25
Female's distance to work (km)	17.86	12.21	0.02	0.03	-0.40	-0.21	0.51	0.52	0.59	0.56	0.08	0.31
Distance to subway (km)	5.77	4.67	-0.04	0.02	-0.16	-0.08	-4.57	-3.82	-4.57	-3.81	-4.58	-3.82
Panel C: Welfare analysis per household (thousand ¥)												
Consumer surplus (+)			-238.9	-55.3	-126.1	-93.2	105.8	75.8	-130.1	20.5	-18.8	-12.7
Toll revenue (+)					143.3	143.3					136.2	136.2
Subway cost (-)							77.6	77.6	77.6	77.6	77.6	77.6
Net welfare			-238.9	-55.3	17.2	50.1	28.2	-1.8	-207.7	-57.1	39.8	45.9

Note:Simulated results based on estimated model parameters in Column (6) of Table 3 and Column (6) of Table 5. The simulation shows counterfactual results for 2014 sample households and houses. The detailed simulation procedure can be found in E. This table shows results with sorting and allowing supply adjustment, hence we allow households' housing choice decisions and travel mode decisions, as well as housing supply to adjust to clear traffic market and housing market. Column (1) shows the baseline results while columns (2) to (6) shows the differences from column (1). Driving restriction prohibits driving in one of five work days. Congestion pricing is ¥1.22 per km to generate same reduction as driving restriction. High-income household are those with income above the median household income. Subway cost per household includes the construction cost and the 30-year operating cost equally shared among 7.2 million households. We apportion 75% it to work commute in our welfare analysis. Toll revenue is the revenue per household from congestion pricing during a 30-year period (to keep a balanced government budget, the toll revenue is recycled uniformly to each household). Net welfare is consumer welfare per household after revenue recycling or tax-funded subway construction and operation.

Online Appendices

Appendix A: Theoretical Model Details

A.1 Spatial Structure

This appendix provides the details for the monocentric city model used to provide illustrative comparative statics for housing market capitalization of transportation policies in Section 2. We consider a monocentric, linear city with a fixed population (N) of rich, N_R, and poor, N_P, residents. All residents work at the urban center (CBD) at location 0, where wage income for the rich is larger: $y_R > y_P$.[45] The rest of urban space is occupied by houses with lot size normalized to 1 and where land rents are remitted to absentee landlords. Housing consumption (in square meters) is provided by perfectly competitive developers facing constant returns to scale. Beyond the residential area is agricultural land, which returns rental value p_a. The model is a closed-city model with intracity, but not intercity migration. Both of these assumptions could be relaxed without affecting the key predictions of the model.[46] A key feature of the model then is that changes in commuting cost will not affect the overall size of the city as reflected by the location of the urban boundary, $\bar{x}$, since the population is fixed and land use per household is also fixed.

A.2 Household Utility Maximization and Housing Demand

Households consume two goods: a numeraire good, c, with unitary price, and housing, $q(x)$, which varies in quantity depending upon the distance from the CBD x. Households seek to maximize utility given income y_d, fixed (θ_m) and variable commuting cost ($w_{d,m}$), which vary by mode $m \in M$ and by household income via differences in the value of time:

$$u_d = \max_{c_{d,m}, q_{d,m}} \quad u\left(c_{d,m}, q_{d,m}\right) \quad \text{s.t.} \quad c_d + p(x) \cdot q_d = y_d - \theta_m - w_{d,m}(x), \quad d = R, P. \tag{A1}$$

The solution to (A1), $\{c^*_{d,m}, q^*_{d,m}\}_{d=R,P}$, determines the pattern of residential locations as well as household-level mode choices, which both helps to determine and, in turn, is affected by the pattern of endogenous congestion that enters the budget constraint via $w_{d,m}$ based upon where car commuters choose to locate. We demonstrate the nature of this endogenous congestion in the next subsection.

A.3 Travel Mode Choice

Two commuting modes exist in the city: personal vehicles with fixed cost θ_C and variable (per-kilometer) cost $w_{d,C}$, and subway with fixed cost θ_S and variable cost $w_{d,S}$. Variable costs include time and pecuniary costs and travel time is monetized by the value of time (VOT): $v_R > v_P$.[47] We begin by assuming that the

[45] Given the linear structure of the city, we assume roads take up no space and all land goes towards housing.

[46] Brueckner (1987) provides an analysis of a monocentric city model with a perfectly competitive supply side for both cases of a closed and open city.

[47] We also assume that fixed costs are larger for car commuting but that variable costs (without congestion) are lower.

subway network covers the entire urban area and then relax this assumption when considering the role of public transportation infrastructure. We ignore the role of congestion in public transportation and focus solely on its effect on car travel.

Car commuting is subject to congestion. Congestion at a given location x depends on the flow of vehicles $n_C(x)$ of rich and poor from the urban boundary to that location:

$$n_C(x) = \int_x^{\bar{x}} \mathbf{1}\{m = C\}_R(x)ds + \int_x^{\bar{x}} \mathbf{1}\{m = C\}_P(x)ds. \tag{A2}$$

What this equation makes clear is that congestion at x depends on the total number of car commuters who live between x and the urban boundary. The flow of car commuters, $n_C(x)$, determines the congestion at point x measured in travel time per unit of travel distance and unit commute cost:

$$t_{d,C}(x) = \nu_d \mathscr{C}(n_C(x)), \quad d = R, P \tag{A3}$$

where ν_d is the value of time for income group, d, and $\mathscr{C}(\cdot)$ is a congestion function with positive first and second derivative.

Another integral is required to calculate total commuting costs for a commuter living at point x as it includes the level of $t_{d,C}(x)$ at everyone point between x and the CBD:

$$w_{d,C}(x) = \int_0^x t_{d,C}(s)ds. \tag{A4}$$

A.4 Market Clearing Conditions and Spatial Equilibrium

Given a mass of households $N = N_P + N_R$ residing and working in the city, a spatial equilibrium is determined by a bid rent function that is the envelope of individual willingness-to-pay for housing based on mode and housing type, keeping the utility for each income type fixed at $\bar{u}_d$, $d = R, P$

$$p^*(x) = \max_{d,m} \left\{ p\left(y_d - \theta_m - w_{d,m}(x), \bar{u}_d\right) \right\}. \tag{A5}$$

Equations (A1) - (A4) make clear the simultaneous determination of housing location and traffic congestion across the city. Solving for congestion at any location x in the city requires knowing the distribution of car users at all points in the city. To understand the shape of the bid rent functions, it is helpful to express the slope, which is the derivative of $\frac{w_{d,C}}{q_{d,m}(x)}$ with respect to x:

$$p'_{d,C}(x) = \frac{t_{d,C}(x)}{q_{d,m}(x)}.$$

For subway commuters, who experience no congestion, the slope of the bid rent function does not change. In residential regions with car commuting, moving from right to left across the region means adding additional car commuters, further increasing per kilometer commuting time costs and steepening the bid rent function.

We now define the spatial behavior of housing prices that a household is willing to pay while maintaining a utility level $\bar{u}_d$ for $d = R, P$. The conditions for a spatial equilibrium are: 1) city population of rich and poor is equal to the sum of the distance within the city that they occupy (given fixed lot size for housing), 2) the equilibrium bid rent and the agricultural rent equate at the urban boundary, 3) budget constraints for each household type and travel mode hold, 4) the equilibrium traffic congestion experienced at each location x in the city is determined by the number of car commuters from x to $\bar{x}$ via $n_c(x)$, and 5) the boundary of residential patterns of rich and poor households using car or subway is determined by the intersections of respective bid rent functions, and the location of these bid rents along the envelope equilibrium bid rent function. The full analytical exposition of these conditions is:

The market clearing conditions for a spatial equilibrium in our model to exist are:

1. All N households are housed within the city, which given fixed lot size per household means that the sum of the subway and car commuting areas yields the total population for rich and poor as: $N_R = x_A + x_C - x_B$ and $N_P = x_B - x_A + \bar{x} - x_C$.

2. Following from the previous condition, since there is fixed lot size per household, the total size of the city, $\bar{x}$ is equal to the total population N, and so the equilibrium bid-rent at the urban boundary $p^*(\bar{x})$ must adjust to equate to the agricultural rent, p_a.

3. Households choose to live in location x so that no alternative location would return higher utility, and given identical preferences, all households in the same income group attain the same level of utility, $\bar{u}_d$:

$$u(c_d, q_d^*(x)) = \bar{u}_d \quad \text{for all} \, x \in [0, \bar{x}], \quad d = R, P.$$

4. The market clearing bid-rent function is the envelope of bid-rent functions across all income and commuting groups:

$$p^*(x) = \max\{p_{d,m}(x)\}, \quad d = R, P, \quad m = C, S.$$

5. Bid rents equate between income and commuting types at some $x \in [0, \bar{x}]$:

$$\begin{aligned} p_{R,S}(x) &= p_{P,S}(x) \\ p_{R,S}(x) &= p_{R,C}(x) \\ p_{R,S}(x) &= p_{P,C}(x) \\ p_{P,S}(x) &= p_{R,C}(x) \\ p_{P,S}(x) &= p_{P,C}(x) \\ p_{R,C}(x) &= p_{P,C}(x), \end{aligned}$$

   where commuting boundaries between each group are defined by intersections that lie along the envelope equilibrium bid-rent function, $p^*(x)$. There must be at least 1 and at most 3 intersections for a spatial equilibrium to exist.

6. Congestion from car commuting at each location $x \in [0, \bar{x}]$ is determined by the density of car commuting between x and $\bar{x}$:

$$n_C(x) = \int_x^{\bar{x}} \mathbf{1}\{m = C\}_R(x) ds + \int_x^{\bar{x}} \mathbf{1}\{m = C\}_P(x) ds$$

The uniqueness of an equilibrium is not guaranteed, and, in particular, the configuration of rich, poor, subway- and car-commuting households will depend upon the relative size of fixed costs of commuting relative to the variable costs, differences in the value of time, and household preferences for housing reflecting the income elasticity of commuting cost and housing demand.

In equilibrium, the bid rent function $p^*(x)$, the housing demand function $q(x)$, the utility level $\bar{u}$, and the urban boundary $\bar{x}$ are determined endogenously based on the level of commuting cost t, incomes y_d, population size N, and agricultural rent p_a.[48] Many urban configurations are possible, but given sufficiently high fixed costs for driving relative to subway, and high variable costs for subway relative driving as well as differences in the value of time to rich versus poor households, a spatial configuration as in Figure A4 may emerge where a mass of rich households live closest to the CBD commuting by subway. Beyond this group, a mass of poor households also commute by subway, followed by a mass of rich households commuting by car that consume more housing than their subway commuting counterparts ($q_{R,S} < q_{R,C}$) to compensate for longer commuting. Finally a mass of car commuting poor households live at the urban boundary given their lower value time, but also consume more housing than their subway commuting counterparts ($q_{P,S} < q_{P,C}$). Bid rents are steeper for rich households than their poorer counterparts for each respective commuting mode because the rich have higher value of time.

Bid-Rent Functions under Heterogeneous Commuting Technology

The functional forms for bid rent functions illustrated in Figure A4 are described below. The bid rent functions for each transportation technology evaluated at the CBD ($x = 0$) are:

$$p^0_{d,S} = \frac{1}{q_{d,S}} [y_d - \theta_S - c_d]$$
$$p^0_{d,C} = \frac{1}{q_{d,C}} [y_d - \theta_C - c_d], \quad d = R, P,$$

where $\frac{y_R}{q_{R,S}}$ is sufficient large compared to $\frac{y_P}{q_{P,S}}$ that $p^0_{R,S} > p^0_{P,S}$. Similarly, the fixed costs of driving are sufficiently high that $\frac{y_R - FC_C}{q_{R,C}} > \frac{y_P - FC_C}{q_{P,S}}$ so $p^0_{R,C} > p^0_{P,C}$, and both are smaller than those for subway.

The bid-rent function for subway riders is:

$$p_{d,S}(x) = \frac{1}{q_{d,S}} [y_d - \theta_S - c_d - \nu_d \xi \cdot x], \quad d = R, P,$$

where ξ is the average subway speed.

[48] Endogenous determination of the urban boundary, $\bar{x}$ comes mechanically through the fixed population size and lot size: lot size multiplied by population yields the boundary where the envelope bid rent function is equal to agricultural rents.

The bid rent function for drivers is:

$$p_{d,C}(x) = \frac{1}{q_{d,C}} \left[y_d - \theta_C - c_d - \nu_d \mathscr{C} \left(\int_x^{\bar{x}} \mathbf{1}\{m=C\}_R(x)ds + \int_x^{\bar{x}} \mathbf{1}\{m=C\}_P(x)ds \right) \right], \quad d = R, P,$$

where $\mathscr{C}()$ is an increasing, convex congestion function of car commuting.

Appendix Figure A3 shows the effect of an exogenous increase in vehicle traffic congestion (e.g., due to road conditions that affect the relationship between traffic density and speed) to illustrate the equilibrium pattern of bid rent functions, housing density and mode choices. The bid rent functions are drawn taking into account congestion, reflecting the fact that the slope and curvature of the car commuting bid-rent functions adjusts based on the extent of car commuting across the city. To make this clear, consider the derivative of the rich, car commuting bid-rent function at a small, arbitrary distance ε to the right of x_B, the boundary between poor subway commuting and rich car commuting:

$$\begin{aligned} p'_{R,C}(x_B + \varepsilon) &= \frac{t_{R,C}(x_B + \varepsilon)}{q_{R,C}} = \frac{\nu_R}{q_{R,C}} \left[\mathscr{C}\left(n_C\left(x_B\right) - \varepsilon\right)\right] \\ &\approx \frac{\nu_R}{q_{R,C}} \left[\mathscr{C}\left(n_C\left(x_B\right)\right) - \varepsilon \mathscr{C}'\left(n_C\left(x_B\right)\right)\right] > p'_{R,C}(x_B), \end{aligned}$$

where ε also corresponds to the mass of commuters living along that distance given the assumption of fixed lot size at 1, and where $q_{R,C}$ is fixed as mentioned above. The second line is then an approximation to the change in the bid-rent, which is comprised of the congestion from the mass of all car commuters (rich and poor) at the modal boundary, x_B where commuting switches from car to subway (moving from right to left) less the congestion from the mass of rich car commuters living between x_B and $x_B + \varepsilon$. This demonstrates that a change in endogenous congestion in the model has two effects: it steepens the bid rent curve overall, and the curve itself gets steeper after passing through residential areas with car commuters as the flow of vehicles onto the roadway builds up.

A.5 Policy Approaches

We consider the effect of a set of transportation policies on the urban structure described above to motivate our empirical work (see Appendix B.1 for the specific policies adopted in Beijing). While there are many potential equilibrium spatial configurations for the city laid out depending on model parameters, we calibrate the parameters of the model to a case in which the rich taking the subway to work live closest to the CBD, the poor taking the subway live in the next area, then the rich taking cars, then the poor taking cars and finally agricultural land beyond the urban boundary as can be seen in panel (a) of Figure A4.[49] LeRoy and Sonstelie (1983) demonstrate that the urban configuration can be explained, in part, by the relation between the income elasticity of commuting costs relative to the income elasticity of housing demand. The figure is consistent

[49]The bid rent curve is convex in the standard monocentric city model where the travel cost is assumed to linear in distance: prices do not need to fall as fast as the increase in travel cost to keep residents indifferent since they are compensated by living in a larger house the further they live away from the city center. The bid rent curve becomes concave only if the travel cost is sufficiently convex in distance. To ease exposition, we draw linear bid-rent curves in the figures.

with the case where the income elasticity of commuting costs is larger than the income elasticity of housing demand. therefore the rich outbid the poor to live close to the city center to save commuting costs.

Congestion Pricing. First we consider a typical first-best approach: a per-kilometer congestion charge. The optimal level would be equal to the marginal external cost of congestion and can be derived from differentiating (A4) with respect to $n_C(x)$ giving the increased cost from one additional car commuter. Multiplied by the number of car commuters, this yields:

$$\tau_C(x) = \left(v_R \frac{n_{R,C}(x)}{n_C(x)} + v_P \frac{n_{P,C}(x)}{n_C(x)} \right) \mathscr{C}'\left(n_C(x)\right). \tag{A6}$$

The revenue from congestion pricing can then be recycled lump sum to each resident of the city. Panel (b) of Figure A4 shows the effect of the congestion pricing on spatial equilibrium in this hypothetical city. Due to the recycling of the revenue, the bid rent curves shift up for subway users. Under the uniform recycling of the revenue, the shift is larger for the poor than for the rich due to the smaller property size among the poor (the denominator of the intercept) as shown in Appendix A. The intercept of the bid rent curves for car users moves up as well. For poor drivers, the slope of the bid rent curve steepens as the congestion toll defined above would be larger than the savings from improved speed (due to their low VOT), hence leading to a higher travel cost per unit of distance (the numerator of the slope). For richer drivers, the bid recent curve would be flatter as the congestion toll would be smaller than the savings from improve speed (due to high VOT). However, the curve to the right of x_B' becomes steeper as it moves to x_B' from the right. This is due to the fact that congestion worsens as it is closer to x_B' from the right, leading to an increasing unit travel cost.

There are two competing forces at work that affect the spatial pattern of residential locations. First, congestion pricing increases the unit travel cost and incentivizes residents to move closer, hence bidding up property prices near the city center. Second, the reduction in congestion leads to time savings and reduces the travel cost. However, due to the differences in VOT, the time saving is more valuable to the rich than to the poor. That is, the second force is relatively stronger compared to the first force for the rich than for the poor. Given the initial spatial configuration, congestion pricing results in some poor resident shifting away from driving to subway while moving from the outer ring to the inner ring. At the same time, some rich residents move out of the inner ring and switch to driving while living in larger houses. If congestion pricing or the cost of driving increases enough, the poor may occupy the city center as in the case when driving is prohibitively expensive for the poor LeRoy and Sonstelie (1983).

Subway Expansion. Panel (a) of Figure A5 considers subway expansion. This can be incorporated into this theoretical framework by making subway costs approach infinity beyond a desired distance x. While the choice of reference point is arbitrary, consider the effect of constraining transit to $\bar{x}_B$ in panel (a) of Figure A5. Given the fixed supply of housing, the constraint of public transit from x_B in panel (a) of Figure A4 to $\bar{x}_B$ shifts the mass of poor subway commuters $\bar{x}_B - x_B$ to the poor car commuting region. This increases congestion to the left of x_B for all car commuters, steepening the slope of the bid rent curves to the left of x_B more for the rich than for the poor due to the high VOT among the rich. In the extreme case of removing all subway from the city, the bid rent curve for the rich would become even steeper as it gets closer to the city as the congestion worsens. Only the rich will occupy the city center. The results are consistent with Glaeser et al. (2008) which show that better public transportation leads more poor to live in the city center.

Driving Restriction. Finally, we consider the effect of raising the cost of driving via a driving restriction. In practice, the driving restriction only bans a portion of the cars from driving each day. We assume that during those days, residents need to take the subway to work. This would imply that the car commuters would need to pay the fixed cost of two modes, while the variable cost would be a weighted sum of the two modes. Panel (b) of Figure A5 shows the effect of the driving restriction. Due to the increase in the fixed cost for car commuters, the intercept of the bid rent curves shifts down, more so for the poor than for the rich (the denominator being larger for the rich). The change in the slope for the car commuters is subjects to two countervailing forces. On the one hand, the added variable cost (due to the higher variable cost when using the subway) will increase the slope. On the other hand, congestion reduction to the left of x'_B will reduce the slope, more so for the rich than for the poor. The first force likely dominants.

The impact of the policy is that the rich reduce car commuting $(x'_A - x_A)$ by more than the poor $(x'_C - x_C)$.

Welfare. While the welfare implications from this stylized example are probably less informative to real world policy applications than the empirical exercises performed in Section 6, Figures A4 and A5 yield an important observation: because changes in commuting costs with respect to income induce changes in the envelope equilibrium bid-rent function in each panel, there are key welfare effects of changes in transportation that capitalize into housing values reflected by the movement up and down of the indicated bid rent functions. Put simply, an approximation to total welfare is the sum of equilibrium rents paid:[50] $\int_0^{\bar{x}} p^*(s)ds$. This can be visualized as the area under the equilibrium bid rent envelope in the figures: when the envelope is lower than the baseline under a given policy scenario, then aggregate rents (and thus welfare) is lower, and visa versa. Considering Figure A5 panel (b), the effect of the driving restriction seems to lower the sum of rents by more than it is increased as the envelope is lower beyond x'_B. This accounts for a larger area than the increase in the level of the equilibrium bid-rent to the left of x'_B. In contrast, the overall effect of congestion pricing in Figure A4 panel (b) is to increase the equilibrium bid-rents envelope at all points in the city because congestion reduction flattens bid rents and the redistribution of the toll revenues increases their value for subway commuters. This points to an important general equilibrium effect of transportation policies in cities, where their benefits are capitalized into the housing market and provide additional welfare gain relative to

[50]To be precise, this provides the sum of willingness-to-pay. Changes in the transportation system may induce changes in consumption with cost implications. If this is provided by perfectly competitive markets, we may assume that equilibrium prices reflect these costs. This logic, the Henry George Theorem, underlies the approach of using changes in land values to uncover the benefits of public good investments (Stiglitz, 1977; Arnott and Stiglitz, 1979). If transportation policies create or remove welfare reducing distortions, this will be reflected in relative changes in bid rent curves. Albouy and Farahani (2017) show that the value of infrastructure could be underestimated using this approach and argue for a more broad method to incorporate imperfect mobility, federal taxes, and non-traded production.

a driving restriction beyond a partial equilibrium framework on the transportation sector alone as shown in Appendix Figure 1. We explore these effects in greater detail in the simulations based on our structural model below.

Appendix B: Policy Background and Data

B.1 Policy Background

During the last four decades, China has witnessed the largest rural to urban migration in human history: urban population increased from 171 million (about 18% of total population) in 1978 to 823 million (nearly 60% of total population) by the end of 2018. After the turn of the century, vehicle ownership increased dramatically: total sales of new passenger vehicle grew from 0.7 million units to nearly 24 million units in 2018. The rapid growth in urbanization and vehicle ownership has overwhelmed the road infrastructure and public transit, leading to serious traffic congestion and exacerbating severe air pollution in all major urban areas across the country. Similar challenges are observed in large cities in other developing and especially fast-growing countries as well. Beijing has been ahead of most other urban centers in China in terms of growth in population, household income, and vehicle ownership. Between 2001 and 2018, Beijing experienced a 56 percent increase in population while household disposable income increased from about \$1,500 to nearly \$9,000 per year, and the vehicle stock has increased from one million to over six million (See Appendix Figure A1).[51]

The central and municipal governments in China have pursued a series of policies to address traffic congestion. In Beijing, these policies include a driving restriction, vehicle purchase restriction, and transportation infrastructure investment, The driving restrict started as part of Beijing's effort to prepare for the 2008 Summer Olympics. It initially restricted half of the vehicles from driving on a given weekday based on their license plate. After the Olympics concluded, the restriction was relaxed to one day a week during weekdays depending on the last digit of the license plate number.[52] In an attempt to curb the growth in vehicle ownership, the Beijing municipal government adopted a purchase quota system for new vehicles in 2011 by capping the number of new vehicle sales. About 20,000 new licences are distributed each month through non-transferable lotteries during 2011 and 2013 and the monthly quota was reduced to about 12,000 after 2013. Winning the lottery has become increasingly difficult: the winning odds have decreased from 1:10 in early 2012 to nearly 1:2000 in 2018 as the pool of lottery participants increases dramatically and the cap tightens over time (Xiao et al., 2017; Li, 2018; Liu et al., 2020). Along with demand-side strategies, the Beijing municipal government

[51] The consumer price index increased by 50% from 2001 to 2018. Among the six million vehicles in Beijing, about five million are owned by households. The household vehicle ownership rate is about 0.6 cars per household in Beijing, comparing to 0.46 in New York city and 1.16 in the U.S. from 2010 U.S. Census.

[52] Police vehicles, buses, municipal street cleaning vehicles, and taxi are exempt from the policy. Athens, Greece implemented the first of driving restrictions in 1982 and since then, at least a dozen other large cities in the world have adopted similar policies including Bogotá, Mexico City and New Delhi. The impacts of these policies have been mixed (Davis, 2008; Viard and Fu, 2015; Carrillo et al., 2016; Zhang et al., 2017).

has also invested heavily in transportation infrastructure. From 2007 to 2018, 16 new subway lines were built with a combined length of over 500km (See Appendix Figure A2 for subway maps over time). By the end of 2019, the Beijing Subway is the world's longest and busiest subway system with a total length of nearly 700km, and daily ridership over 10 million.[53]

Despite these policy efforts, traffic congestion continues to be a pressing issue in Beijing: the average traffic speed was 24.6km/h during peak hours (7-9am and 5-7pm) in 2019 according to the 2020 Beijing Transportation Report. These policies fail to address the root cause of traffic congestion, the mispricing of road capacity. By recognizing traffic congestion as a classic externality, (Vickrey, 1959, 1963) proposed congestion pricing as the first-best policy to address traffic congestion. Despite being continuously advocated by economists since then, congestion pricing has only limited adoption in practice with many failed attempts around the world largely due to technical feasibility and especially political acceptability.[54] The Beijing municipal government recently announced a plan to introduce road pricing in the near future while soliciting feedback from experts and the general public (Yang et al., 2019).

B.2 Choice Set Construction

We define the choice set to include six modes for a trip: *Walk*, *Bike*, *Bus*, *Subway*, *Car*, and *Taxi*. In principle, a traveler could take one of the six modes alone or any combination of them, which would expand the choice set significantly. For subway and bus, we allow commuters to walk to and from subway stations and bus stops. For the other four modes, we eschew multi-mode commuting to make the number of alternatives tractable and because trips single-mode trips account for over 95% of all trips in our data. The construction of the travel time and travel distance via API or GIS for each mode is illustrated in Appendix Figure A7 and the detailed description is provided in Appendix.[55] Appendix Figure A8 shows travel time and cost of six routes for a particular trip based on the procedure.

The size of the choice set varies across commuters and trips based on household demographics and trip characteristics. Car mode is available for a given household member only if the household owns a vehicle and

[53] Many other cities in China are also rapidly building and expanding their subway systems. The number of cities with a subway system in mainland China increased from four to over 40 from 2000 to 2019, and the total urban rail network reached over 6,700 kilometers of by the end of 2019. See Anderson (2014); Yang et al. (2018); Gu et al. (2020) for recent analysis on the impact of subway expansion on traffic congestion.

[54] Vickrey (1963) asserted: "... in no other major area are pricing practices so irrational, so out of date, and so conducive to waste as in urban transportation." This statement remains largely true today. Singapore first adopted congestion pricing in 1975 and is now transitioning to the 4th generation GPS-based system in 2020. During the last 15 years, several European cities (London, Milan, Stockholm, and Gothenburg) have successfully implemented various congestion pricing schemes. After several proposals over the years, New York State legislature has approved a congestion pricing plan for New York City. Pending approval by the Federal Highway Administration, New York City will become the first city in the US to enact congestion pricing in 2021.

[55] The same procedure was used to construct the travel choice set for home-work commutes in the housing data. Given the rapid expansion of the subway network during our data period, we construct the subway time and hence EV_{ij} term using the subway network two-year ahead in our baseline analysis. The subway construction needs to go through a long process including the approval from the central government, impacts evaluation, construction, and testing Yang et al. (2018); Gu et al. (2020). It takes 2-5 years from the start of the construction to the operation. The public announcement of subway station locations can be a few months ahead of the construction. We also conduct a robustness check using a one-year projection window in constructing subway time.

the member has a driver's license.[56] Walk, bike, and taxi modes are available for all trips. Bus availability is determined by the home and job locations and the mode is removed from the choice set if Gaode Maps API fails to provide any bus route, indicating the lack of the public bus service in the vicinity. We allow the subway to be available for each traveler based on the nearest station and assuming that they walk to/from the nearest subway stations to the origin and the destination.

We construct the monetary travel cost for each mode as follows. The monetary cost for walking is zero. For biking, the cost is zero for households who own a bike. For non-bike owners, the cost of biking is the rental price (free for the first hour and then ¥1 per hour with ¥10 as the maximum payment for 24 hours). The bus fare is set based on municipal bus rates at 0 for senior citizens, ¥0.2 for students, ¥0.4 for people with public transportation cards, and ¥1 for people without public transportation cards. The baseline subway cost per trip is set by the public transport authority at ¥2 and adjusted by the type of public transportation card the traveler holds. Fuel cost is a major component of the monetary cost associated with driving. Based on the average fuel economy reported by vehicle owners in BHTS, we use 0.094 liter/km (10.6 km/liter) for 2010, and 0.118 liter/km (8.5 km/liter) for 2014. Gasoline prices are 6.87 ¥/liter in 2010 and 7.54 ¥/liter in 2014. The taxi fee is based on the following rules: in 2010, ¥10 for the first 3 km, and then additional ¥2 per km and ¥1 as the gasoline fee; and in 2014, ¥13 for the first 3 km, and then additional ¥2.3 per km plus ¥1 as the gasoline fee.

B.3 Housing Data

Appendix Figure A14 shows the distance to work by gender and how the boxplots of the distance to work by year for males borrowers and female borrowers, separately. On average, female borrowers have a slightly shorter commute than for male borrowers The average distance to work has increased from about 10km to 12km over time, reflecting the expansion of the city and transportation infrastructure.

As discussed above, the government-back mortgage program was eligible only for those with formal employment. Although the mortgage data may have a good representation of the middle-class in Beijing it under-represents the two ends of the income distribution (e.g., low-income households without employment or rich households who do not take loans to finance purchases). To increase the representativeness of the re-weighted mortgage data, we use two larger data sets of resales from real estate listings and new sales from property registrations, respectively for the matching benchmark. Resales data come from the largest real estate brokerage company that has a 40% market share in the resale market during our sample period. New sales data, accounting for about 90% new property sales, are from real property registration records from Beijing Municipal Commission of Housing and Urban-Rural Development, a government agency that records housing transactions.[57] New sales and resales account for 43% and 57% of the Beijing housing market, respectively during our sample period. Within the 6th ring road, the two shares are 37% and 63%. In the mortgage data, the sales of new properties account for about 29% of all sales throughout the city and 25% within the 6th

[56] Car rental is not common in Beijing and the mode share of using rental car is nearly zero.

[57] The new property sales data do not include transactions for employer-provided/subsidized housing.

ring road. We apply entropy method (Hainmueller, 2012), which solves for optimal weights as a constrained optimization question:

$$\min_{w_i} H(w) = \sum_i h(w_i) = \sum_i w_i \log\left(\frac{w_i}{q_i}\right) \tag{A7}$$

subject to balance and normalizing constraints:

$$\sum\nolimits_{i\in \text{new properties}} w_i c_{ri}(X_i) = m_{r,\text{registration data}}$$
$$\sum\nolimits_{i\in \text{resales}} w_i c_{ri}(X_i) = m_{r,\text{listing data}}$$
$$\sum\nolimits_i w_i = I, w_i \geq 0 \text{ for all } i.$$
$$\frac{\sum_{i\in \text{new properties}} w_i}{\sum_{i\in \text{resales}} w_i} = \text{true new property-rasale ratio}$$

where our optimization objective h is the Kubelick divergence with base weight $q_i = 1$ in our particular case. $m_{r,\text{registration data}}$ and $m_{r,\text{listing data}}$ is our matching objective, the true covariate moments from registration data and real-estate listing datasets. The matching covariates include housing prices, sizes, building ages, and distances to city center. We match first two moments (mean and variances). We additionally impose a condition such that the ratio of new properties to resales is the same as what we have for the Beijing housing market in the same period. We obtain the optimal weights using the entropy package in STATA.

To further gauge the representativeness of the re-weighted mortgage data, Appendix Figures A15 compares re-weighted the mortgage data with registration and real-estate listings dataset. For both resales and new sales, properties in the mortgage data have a good match with the data in registration data and real-estate listings. Hence in all the analysis, we reweight the mortgage data based on the two larger data sets to improve the representativeness of our sample.

Appendix C: Reduced-form Evidence

This section presents reduced-form evidence of the impact of car driving restriction policy (CDR) on the housing market. We examine the price gradient with respect to subway proximity as well as household sorting behavior.

Price Gradient with respect to Subway Proximity To further examine the pattern shown in Figure 5, we conduct regression analysis to better address confounding factors. A number of confounding factors could undermine identification of the causal relationship between housing price gradients and the driving restriction policy. For example, if amenities improve over time in locations near subway stations more than in locations that are farther away from subway stations, this would result in a larger price increase for properties close to subway stations, leading to an overestimation of the true impact of the policy. On the other hand, if the changes in dis-amenities such as congestion or noise follow the aforementioned pattern, we would underestimate the impact of the policy. Causal identification requires an assumption that the housing price gradient with respect to the distance to the nearest subway station would be unchanged in the absence of the driving restriction policy. We test the plausibility of this assumption by examining trends in price gradients in the periods leading up to the policy based on an event study framework:

$$\ln\text{Price}_{jt} = \sum_{k=-24}^{24} \beta_k \times \ln \text{D}_{jt} \times \mathbb{1}(t=k) + \text{x}'_{jt}\gamma + \varepsilon_{jt} \tag{A8}$$

where j denotes a property and t denotes a month. The outcome variable is the unit price (¥per m^2) in logarithm. We allow the slope of the price gradient β's to vary over time. The regression includes a flexible set of controls (x_{jt}) that include neighborhood fixed effects, year by month fixed effects, and complex-level attributes.[58] Standard errors are clustered at the neighborhood level to allow for correlations among the properties in the same neighborhood (e.g., due to unobservables).

Appendix Figure A12 shows the coefficient estimates of β_k with the coefficients varying by quarter. There does not appear to have a pre-existing trend before the policy, alleviating the concern of the time-varying and location-specific unobservables discussed above. While there is not a clear relationship between subway proximity and housing price before the policy, there is a clear downward shift in the slope of price gradient. Moreover, the negative relationship between subway distance and housing price becomes stronger over time. The increasingly larger impact over time after the policy could be driven by the fact that the uncertainty in terms of the policy is reduced over time and that the enforcement has been tightened over time.

One additional concern for identification is that as the subway network expands and the benefit increases, commuters may have a stronger preference for being close to subway. Appendix Figure A16 shows the timeline of the subway expansion which started in 2007 but accelerated after 2009. Subway construction usually starts 2-3 years before the opening and the announcements are even earlier. If our results are driven by the subway expansion, there should have been a steepening of the slope before the driving restriction. To further address this issue, we include in the regressions a measure of subway density and it is constructed as the inverse distance weighted number of subway stations from a given location following Li et al. (2019). This measure can be considered as the number of subway stations per unit area centered around a given housing unit and it increases as the subway network expands.

Appendix Table A1 provides the regression results for six specifications. The parameter of interest is the interaction between subway distance and the policy dummy. The third column corresponds to the specification with the event study graph in Appendix Figure A12. Adding neighborhood fixed effects to control for neighborhood amenities significantly changes both coefficient estimates from column (1) to column (2). However, adding the rich set of complex-level variables barely changes the results. The fourth column is a weighted regression in order to make the result more representative of the universe housing transactions. We re-weight the sample based on the large data on real estate listings and new property registrations to match

[58] Complex-level attributes include complex age, floor to area ratio, green space ratio, land area of the complex, property management fee (HOA fee), the number of units in the complex, and the number of buildings in the complex.

the price distribution the houses using entropy balancing (Hainmueller, 2012). The last two columns include the subway density measure as an additional control. The coefficient estimates on them are positive but not precise. The results from the last five columns are all qualitatively the same: the driving restriction policy increases the price premium for properties that are closer to subway.

Appendix Figure A13 provides a falsification test by randomizing treatment status (before or after the driving restriction policy) of each transaction while keeping the share of post-policy transactions fixed.[59] The figure shows the histogram of the coefficient estimates of the interaction term between distance and treatment dummy from 500 iterations. The estimate from the true sample (-0.019) lies outside of 99 percentile of the distribution. This further alleviates the concern that the estimated impact might be driven by unobservables.

Evidence for Household Sorting The change in the housing price gradient with respect to subway proximity highlights the impact of the policy on household location choices. To understand the underlying sorting process and how the policy impact differs by income groups, we examine household location choices relative to subway and job locations. Appendix Table A2 provides two sets of regressions. The dependent variable in the first three columns is the distance of the property to the nearest subway station while that in the last three columns is the distance of the property to the job location of the borrower(s). The key explanatory variables are household income and its interaction with the policy dummy. The coefficient estimates on the interaction term in the first two columns suggest that after the policy, high-income households tend to purchase properties that are closer to subway than before the policy. The third column is a weighted regression which produces imprecise estimates but with the same directions as the first two columns. The last three columns examine the impact on housing choices with respect to job location. The coefficient estimates suggest that high-income households live further away from where they work compared to low-income households. After the policy, high-income households tend to choose properties closer to job locations relative to before the policy. The results are robust to using the distance to the job location of the primary borrower only.

[59] We take random draws from a uniform distribution and replace the draws with an indicator variable so that the indicator variable has the same mean as the treatment variable. This indicator variable is the new treatment variable in the estimations. This effectively randomizes the transaction date for the properties.

Appendix D: Proof of Sorting Equilibrium

Here we abstract from uniqueness associated with endogenous housing prices. Propositions 1 and 2 of Bayer et al. (2004) demonstrate that given the assumptions laid out below regarding the functional form of utility and the error term, a unique vector of prices clears the market and results in a unique sorting equilibrium. The form of that proof applies Brouwer's Fixed Point Theorem as below, but on the basis of an element-by-element inverse of the demand function for prices. The sufficient condition for uniqueness is that the sum of the partial derivatives of inverse demand function with respect to prices are bounded by $(-1,1)$. The unique set of prices then implies a unique set of choice probabilities that imply a unique sorting equilibrium. We proceed to demonstrate existence and uniqueness of the equilibrium in the presence of endogenous congestion.

We assume utility from housing as:

$$U_{ij} = \mathbf{x}_j \beta_i + \phi_i EV_{ij} + \varepsilon_{ij}, \tag{A9}$$

where $x_j =$ are exogenous attributes of housing location j, and EV_{ij} is the matching value of home-work commute for housing location j for household i.[60] EV_{ij} is constructed as the logarithm as the sum of indirect utility from each commuting mode:

$$EV_{ij} = \log \left(\sum_{m \in M_{ij}, m \neq car} \exp \left\{ \mathbf{Y}_m \lambda_i \right\} + \exp \left\{ \mathbf{Y}_{car} \lambda_i + \gamma_1 \frac{dist_{ijcar}}{\bar{v}_{ijcar} \cdot v\left(R_{car}\right)} \right\} \right) \tag{A10}$$

$Y_m =$ are exogenous attributes of individuals and driving modes m in the mode choice set (cost, alternative specfic constants, and demographic characteristics), M_{ij} of household i at housing location j. The second exponentiated term is the indirect utility from driving, which depends on exogenous attributes and endogenous travel time, which is the ratio of driving distance to baseline travel speeds from Baidu, v_{ijcar}.[61]

Here the term $v\left(R_{car}\right)$ is a single-valued speed adjustment factor that depends on the share of households in Beijing choosing driving as their commuting mode, R_{car}. Travel times therefore adjust in response to changes in the share of drivers.

Each exogenous attribute, k varies by individuals

$$\beta_{ik} = \bar{\beta}_k + \mathbf{z}_i \beta_k, \quad \lambda_{ik} = \bar{\lambda}_k + \mathbf{z}_i \lambda k,$$

where $\mathbf{z}_i$ is a vector of household i's attributes.

[60] As noted in the preceding paragraph, we omit the housing price from this equation although the results hold with endogenous housing prices by the logic laid out there.

[61] The coefficient vector λ_i here nests the parameters other than those account for travel time in equation (3) of the sorting model.

Assumptions

- Coefficient on driving travel time γ_1 terms and on travel time (which is determined by speed) is the same across individuals
- Unobserved vector of preferences ε_i observed by all other homebuyers through a static, simultaneous-move game following Nash Equilibrium concept
- Continuum of individuals with observed characteristics z_i to allow for integration out
- Speed changes from changes in the number of drivers affect congestion in every part of the city by the same factor $v(R_{car})$
- ε is drawn from a continuous, well-defined distribution function

Probability of choosing car,

$$R_{ijcar} = r_{ij}(\mathbf{z}_i, \mathbf{Y}_{ijm}, \bar{v}_{ij}, v(R_{car}); \lambda, \gamma_1) \quad \forall i, j \tag{A11}$$

is a function of household demographics, mode attributes including baseline speed, and the endogenous speed adjustment factor.

Aggregating these probabilities across individual car commuters yields:

$$R_{car} = \sum_j \sum_i r_{ij}(\mathbf{z}_i, \mathbf{Y}_{ijm}, \bar{v}_{ij}, v(R_{car}); \lambda, \gamma_1) \tag{A12}$$

Definition 1. *A sorting equilibrium is a set of location and commuting decisions that are optimal given the location and commuting decisions of all other individuals in Beijing.*

(A12) defines a single-valued function R that maps $[0,1]$ into itself and therefore a fixed point allowing the following proposition.

Proposition 1. *If U_{ij} is defined as in (A9), a sorting equilibrium exists for all i, j.*

Proof. The equations above show how (A12) is a continuous mapping of a closed and bounded interval onto itself. The existence of a fixed point follows from Brower's Fixed Point theorem. Any fixed point R^* is associated with a unique set of choice probabilities of driving in (A11) that satisfy the conditions for a sorting equilibrium. The existence of this fixed point implies the existence of a sorting equilibrium. ■

To define uniqueness of the equilibrium, it is helpful to define an implicit function of A12

$$\Phi(\mathbf{z}_i, \mathbf{Y}_{ijm}, \bar{v}_{ij}, v(R_{car}); \lambda, \gamma_1) = R_{car} - r(\mathbf{z}_i, \mathbf{Y}_{ijm}, \bar{v}_{ij}, v(R_{car}); \lambda, \gamma_1) \tag{A13}$$

Proposition 2. *If U_{ij} is defined as in (A9), and $\gamma_1 < 0$ a sorting equilibrium is unique.*

Proof. Proof of uniqueness is simplified by the fact that (A12) is a single-valued function of R onto itself. So long as a solution exists, it must be unique. ■

Appendix E: Simulation Approach

In the benchmark simulations, we assume a "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 expansion of subway network. In the robustness check in Table A6, we allow the supply side to adjust using a price elasticity of two (Saiz, 2010; Wang et al., 2012). We use observations in 2014 to conduct simulations and set the baseline scenario as one without driving restriction, no congestion pricing, and under the 2008 subway network. This baseline scenario is not observed in the data so we need to simulate the housing and travel mode choices. We use the following simulation algorithms to simulate outcomes under the baseline and other policy scenarios.

Following Yang et al. (2019), we estimate the relationship between traffic speed and density by leveraging the plausibly exogenous variation in traffic density induced by the driving restriction policy in Appendix Table A3.[62] Based on hourly traffic speed and density data from all major roads (freeways and expressways, but not the secondary roads), the elasticity of traffic speed with respect to density is estimated to be -0.62 within the 6th ring road during peak hours. Because the data does not cover secondary roads where traffic congestion tends to be worse, this estimate is likely a lower bound for the elasticity in the whole city. We restrict the sample to observations with traffic density larger than 35 (cars/lane-km), the elasticity estimate becomes -1.1. The average speed among these observations is about 30km/h, close to the city-wide average speed during peak hours. Hence we use -1.1 as the speed-density elasticity in our simulations.[63]

The simulation algorithm starts with an initial observed housing price vector and road congestion factor, which will be endogenously determined by the algorithm in each iteration. Each iteration has an inner loop to solve for housing location choices taking the matching value of home-work commute, EV_{ij} defined in equation (5), as well as market clearing house prices, and the outer loop to simulate consistent congestion factor. Under each policy scenario, the inner loop holds congestion factor constant, and iteratively solves for the travel mode choices and housing location choices that give rise to new congestion level, and hence travel time for driving. The outer loop repeats until finding a consistent congestion factor. The changes in travel time and costs due to the policy changes affect the matching value of home-work commute, EV_{ij}, for each property. Under driving restriction, we calculate EV_{ij} by assuming driving is not an option one in five days. This would make the driving mode to be less attractive and properties that are closer to subway or job centers more attractive. Congestion pricing enters EV_{ij} by increasing the monetary cost of driving. The outer loop then takes the updated EV_{ij} as input and allows households to adjust housing locations. The algorithm

[62] The policy restricts some vehicles from driving one day per week during weekdays depending on the last digit of the license plate number. The policy follows a preset rotation schedule in terms of which pair of numbers (1&6, 2&7, 3&8, 4&9, 5&0) is restricted on a given day, and it is not adjusted based on traffic conditions. The policy generates exogenous variation on traffic density due to the fact that the distribution of vehicles is not uniform with respect to the last digit of plate numbers. Vehicles with the license plate ending with number 4 only account for about 2% of all vehicles because the number 4 is considered an unlucky number in Chinese culture. Therefore, when numbers four and nine are restricted, more vehicles are on the road, and congestion tends to be worse than other days.

[63] In practice, there could be route-specific congestion responses from commuters, which we abstract away in our simulations for tractability.

solves for a new price vector that clears the housing market. The iterative procedure results in new congestion levels and a new vector of housing prices. In our setting of a closed city (without outside options), housing prices are only identified up to a constant. So we fix average price of all houses the same so as to partial out price changes as asset shock for all consumers to simplify welfare calculations. A step-by-step simulation algorithm is illustrated below.

We observe the baseline traffic density d_0 and driving speed $\vec{v}_0$. The elasticity of speed with respect to density is e. Model primitives $\{\gamma_1,\gamma_2,\eta,\beta,\alpha,\phi,\theta,\xi\}$ are estimated and and are fixed in simulation. Traffice Speed elasiticity e is exogeneously given. $\vec{p}$ is the observed baseline price vector. Household demographics $\{X^1\}$ and housing attributes $\{X^2\}$ are observed. We also know the travel distance, time, and cost information for different modes of each house-working place pair. Housing choice sets $C(i)$ are fixed in simulations (constant housing supply). We also fix sets of random draw $v_r, r=1,...R$, and $w_q, q=1,...Q$.For each counterfactual scenario:

1. Guess a traffic density level $d_0^{'}$ (e.g., d_0).

2. Given a new density level d^t. Then,

(a) Compute driving speed $\vec{v}^t=\vec{v}_0\left(1+e\left(\frac{d^t}{d_0}-1\right)\right)$;

(b) Update each member k in household i's new commuting time to each house j in household i's choice set based on new driving speed $time^t_{ijk,\text{drive}}=\frac{dist_{ijk,\text{drive}}}{v^t_{ijk}}$(as well as taxi speed $time^t_{ijk,\text{taxi}}$);

(c) Given $time^t_{ijk}$ Calculate expected matching value of home-work commute for member k conditional on house j :

$$EV^t_{ijk}(time)=\frac{1}{R}\sum_{r=1}^{R}\log\left(\sum_m \exp\left(\frac{\text{cost}_{ijk,m}}{\text{hourly wage}_{ik}}\gamma_1+time^t_{ijk,m}\gamma_{2r}+X^1_{ijk,m}\eta_r\right)\right)$$

and member k's probability for driving:

$$R(drive|i,j,k)=\frac{1}{R}\sum_{r=1}^{R}\frac{\exp\left(\frac{\text{cost}_{ijk,drive}}{\text{hourly wage}_{ik}}\gamma_1+time^t_{ij,drive}\gamma_{2r}+X^1_{ijk,drive}\eta_r\right)}{\sum_m \exp\left(\frac{\text{cost}_{ijk,m}}{\text{hourly wage}_{ik}}\gamma_1+time^t_{ijk,m}\gamma_{2r}+X^1_{ijk,m}\eta_r\right)}$$

If we allow sorting, then continue with step (d)-(e). Otherwise skip them and move to step (f);

(d) Given the new expected commuting values, calculate a new house price vector $\vec{p}^t$ such that (1) house demand= house supply, (2) weighted mean house prices are kept constant:

$$\begin{aligned}\frac{1}{Q}\sum_{q=1}^{Q}\sum_{i\in C^{-1}(j)} w_i\frac{\exp\left(\sum_k \phi_{kq}EV^t_{ijk}+\alpha_i p^t_j+X^2_j\beta_i+\xi_j\right)}{\sum_{s\in C(i)}\exp\left(\sum_k \phi_{kq}EV^t_{isk}+\alpha_i p^t_s+X^2_s\beta_i+\xi_s\right)} &= f(w_j,p_j),\ \forall j\in J\\ \text{and mean}\left(\vec{p}^t\right) &= \text{mean}(\vec{p})\end{aligned}$$

if we keep house supply constant, then

$$w^t_j=f(w_j,p_j)=w_j$$

if we allow house suppply to adjust, we assume that house supply adjusts based on a constant elasticity rule:

$$w_j^t = f(w_j, p_j) = w_j \left(1 + e_{w,p}\left(\frac{p_j^t}{\bar{p}_j} - 1\right)\right)$$

(e) Given new $\vec{p}^t, EV^t$, calculate the new housing choice probability

$$\Pr(j|i) = \frac{1}{Q}\sum_{q=1}^{Q} \frac{\exp\left(\sum_k \phi_{kq} EV_{ijk}^t + \alpha_i p_j^t + X_j^2 \beta_i + \xi_j\right)}{\sum_{s \in C(i)} \exp\left(\sum_k \phi_{kq} EV_{isk}^t + \alpha_i p_s^t + X_s^2 \beta_i + \xi_s\right)}$$

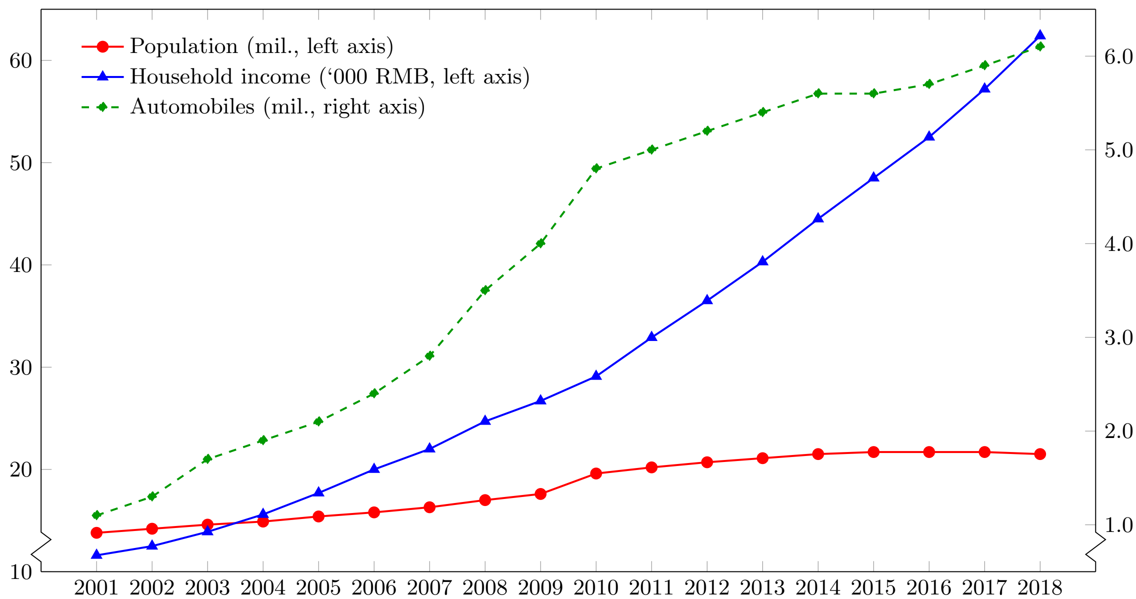
(f) Update the new traffic density:

$$\tilde{d} = \sum_i \sum_j \Pr(j|i)\left[\sum_k R(drive|i,k,j) \times dist_{ijk,\text{drive}}\right]$$

3. If $\left\|\tilde{d} - d^t\right\| < \varepsilon_{tol}$ where ε_{tol} is a pre-set tolerance level, stop. Otherwise, set $d^{t+1} = \varphi d^t + (1-\varphi)\tilde{d}$ for some $\varphi \in (0,1)$ and return to step 2.

Appendix F: Figures & Tables

Figure A1: City Growth in Beijing 2001-2018

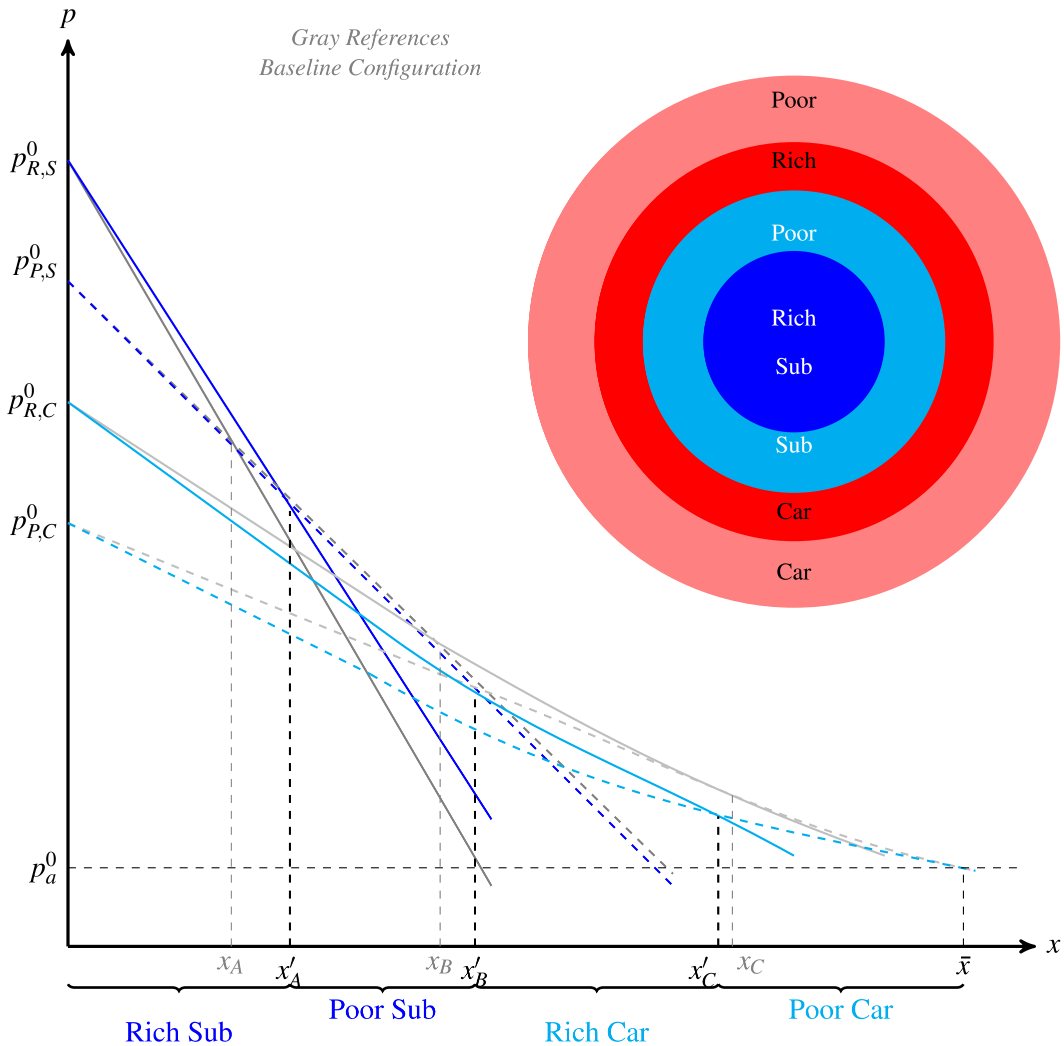


Note: Data come from Beijing Transportation Annual Report The figure plots population, household income, and the number of registered automobiles in Beijing during 2001-2018. Data come from Beijing Transportation Annual Report.

Figure A2: Subway Network Expansion from 2000 to 2020 in Beijing

Note: Subway expansion from 1999 to the end of 2019 in Beijing: from 2 lines to 22 lines. Total mileages increase from ...

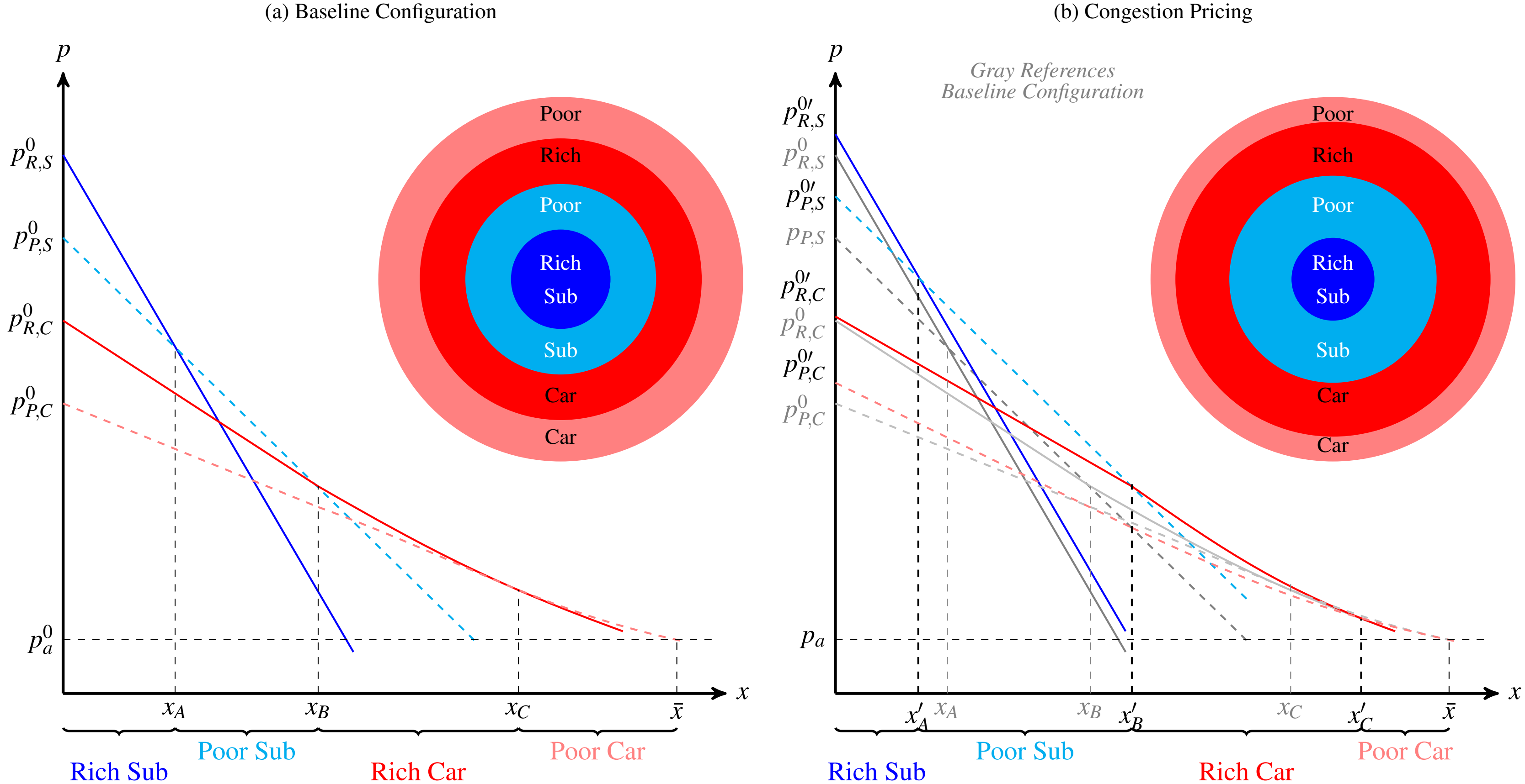
Figure A3: Exogenous Increase of Congestion in Monocentric City Model



Note: The x-axis denotes the distance to city center and the y-axis is the rental price. Concentric circles show the equilibrium pattern of housing location where the linear city is drawn as radially symmetric. Commuters are in two income groups (Rich, *R*, indicated with solid lines, and Poor *P*, indicated with dashed lines) and choose from two modes: car (*C*, in red) and subway (*S*, in blue). The model is calibrated to generate an urban configuration as indicated. Bid-rent curves are steepest for the rich because of their higher value of time. Bid-rent curves are flatter for car commuting because the variable time cost is assumed to be smaller. Values indicated by $p^0_{d,m}$ are the value of bid-rent curves at the origin, while those with a $\prime$. Gray curves reference the baseline configure in panel (a) of Figure A4. Here we consider the effect of an exogenous increase in congestion through a decrease in capacity throughout the city. This steeps the bid rent curves for driving, for the rich more than the poor. It also changes the slope of the subway bid-rent curves by an increase in the fixed demand for housing for the rich subway commuting and a small decrease in the fixed demand of housing for poor subway commuters. The result is to shift more of the rich to subway commuting and small share of the poor are induced to car commuting given changes in housing prices.

Figures & Tables

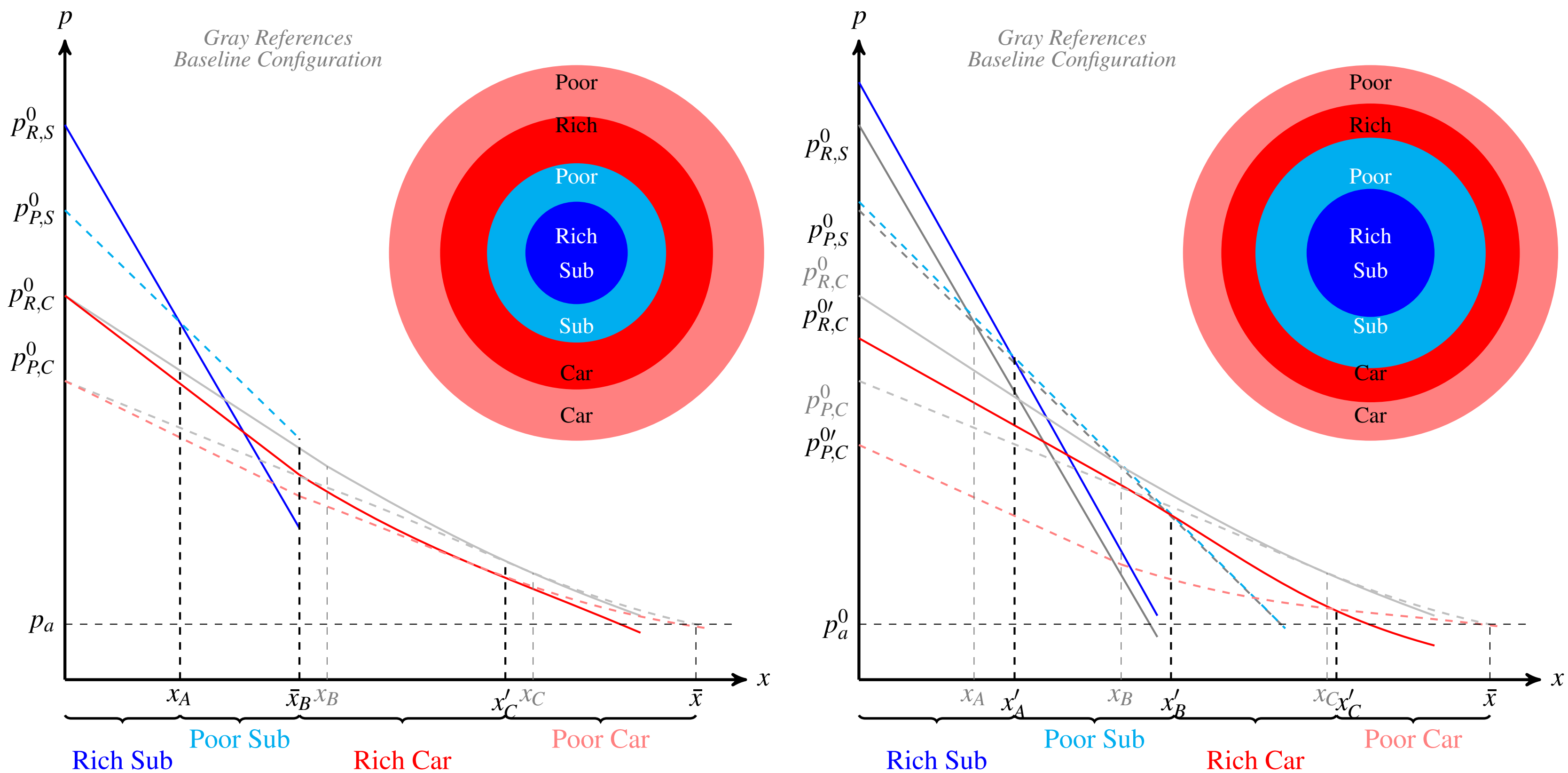
Figure A4: Spatial Equilibrium with Two Modes & Income Heterogeneity: Baseline & Congestion Pricing



Note: The x-axis denotes the distance to city center and the y-axis is the rental price. Concentric circles show the equilibrium pattern of housing location where the linear city is drawn as radially symmetric. Commuters are in two income groups (Rich, R, indicated with solid lines, and Poor P, indicated with dashed lines) and choose from two modes: car (C, in red) and subway (S, in blue). The model is calibrated to generate an urban configuration as indicated. Bid-rent curves are steepest for the rich because of their higher value of time. Bid-rent curves are flatter for car commuting because the variable time cost is assumed to be smaller. Values indicated by $p^0_{d,m}$ are the value of bid-rent curves at the origin, while those with a $\prime$. Gray curves, dashed lines and text in panel (b) reference the baseline configuration in panel (a). Panel (b) shows the effect of congestion pricing in a per-kilometer basis. It increases the y-intercept through lump-sum remittance of toll revenue back to all households. For car commuting, there are offsetting effects: congestion is lower with the toll because there are fewer car commuters, but longer commutes face larger total tolls, making bid rent curves steeper.

Figure A5: Spatial Equilibrium with Two Modes & Income Heterogeneity: Subway & Driving Restriction

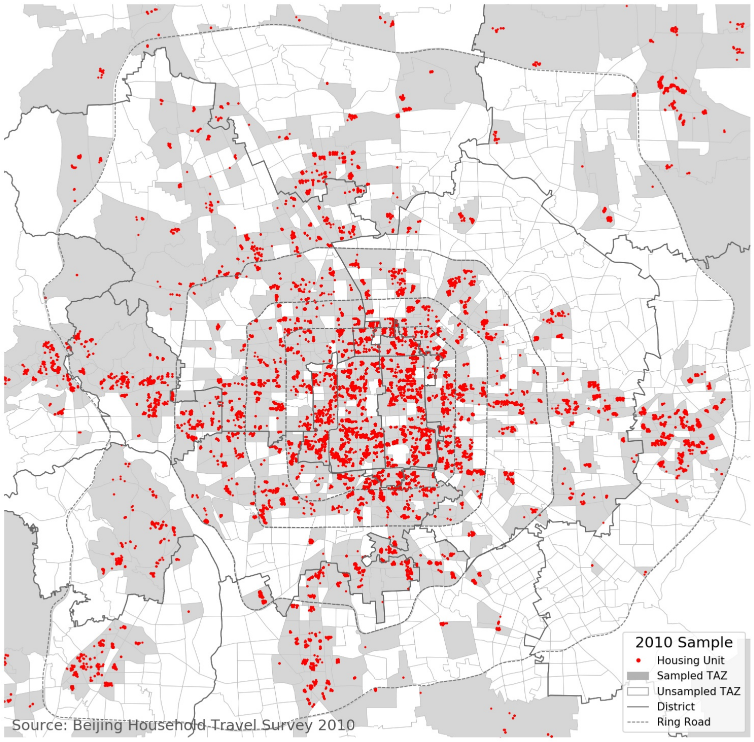
(a) Subway Restricted to $\bar{X}_B$ (b) Driving Restriction



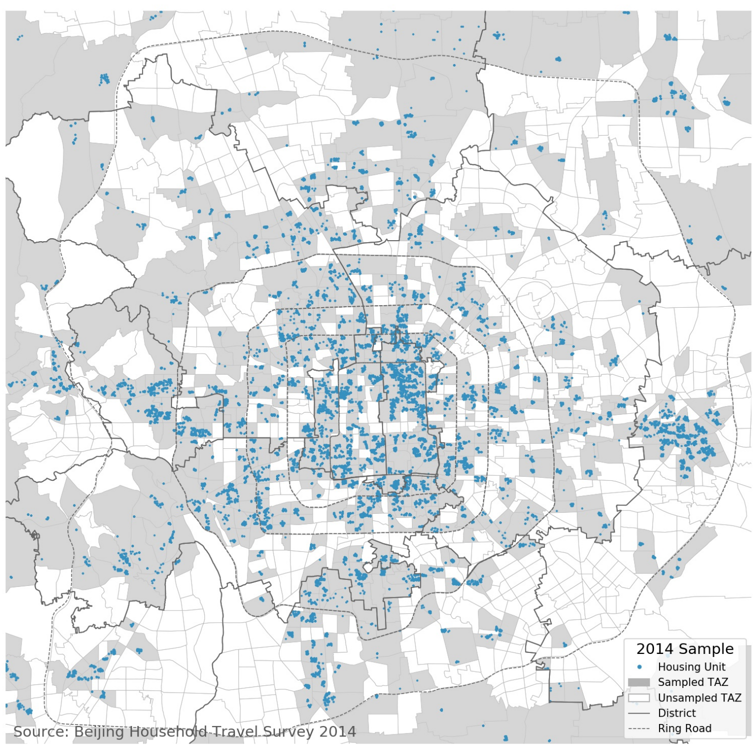
Note: The x-axis denotes the distance to city center and the y-axis is the rental price. Concentric circles show the equilibrium pattern of housing location where the linear city is drawn as radially symmetric. Commuters are in two income groups (Rich, R, indicated with solid lines, and Poor P, indicated with dashed lines) and choose from two modes: car (C, in red) and subway (S, in blue). The model is calibrated to generate an urban configuration as indicated. Bid-rent curves are steepest for the rich because of their higher value of time. Bid-rent curves are flatter for car commuting because the variable time cost is assumed to be smaller. Values indicated by $p^0_{d,m}$ are the value of bid-rent curves at the origin, while $p^{0\prime}_{d,m}$, are the new values at the origin after the policy change. Gray curves reference the baseline configure in panel (a) of Figure A4. Panel (a) shows the effect of restricting the subway network to $\bar{x}$. Comparing this panel to panel (a) of Figure A4 shows the effect of expanding the subway network from $\bar{x}_B$ to x_B. There is no effect of expansion on the bid rents for subway except that they do not extend beyond $\bar{x}_B$ in panel (a) of Figure A4 because the subway has not been built that far. Because expansion allows a larger share of commuters to use the subway, here only from the poor, it induces lower congestion, flattening out the bid-rent curves for driving, for the rich more than the poor because of value of time differences. Panel (b) considers a driving restriction policy, which induces increases in both the fixed and variable costs of driving not remitted to households (unlike congestion pricing). Car commuters will need to incur the fixed cost of both driving and and using subway, and when they cannot drive, they will have to use subway which has a higher variable cost due to time. The bid rent curves for car commuters move down and become steeper because of the change in fixed cost and variable cost of commuting, respectively. The increase in commuting costs is larger for the rich due to their high VOT than for the poor, leading to a larger movement of the rich away from driving to subway.

Figure A6: Beijing Household Travel Survey Samples

(a) 2010 BHTS

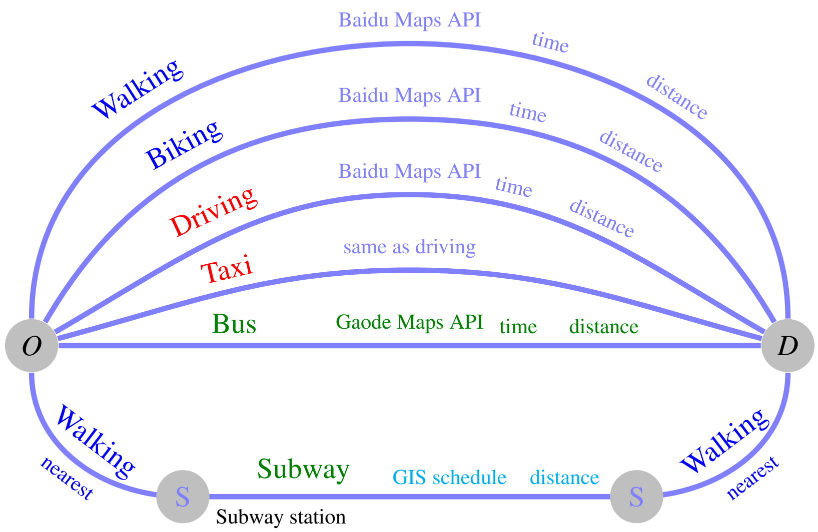


(b) 2014 BHTS



Note: The figures show the home locations of 2010 and 2014 Beijing Household Travel Survey with the 6th ring road, the focus of our analysis. The shaded areas are sampled TAZs. The success rates of geocoding for the home addresses are 97% and 98% for the two years.

Figure A7: Construction of the Travel Choice Set



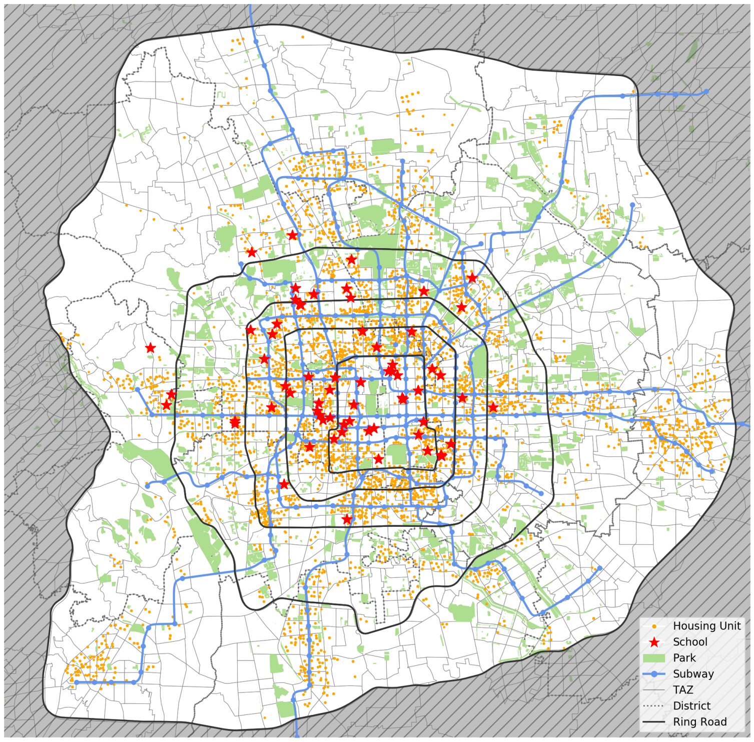
Note: Travel time and distance using walk, bike, car, and taxi are constructed using Baidu Maps API based on the departure time and the day of the week. Travel time and distance are constructed using Gaode Maps API because it provides the number of transfers and walking time between bus stops. Walking time and distance to and from the subway station are provided by Baidu Maps API while the distance from the first station to the last station are calculated using GIS based on the subway network in 2010 and 2014. The corresponding subway time table is used to construct station-to-station travel time. The data queries for car and bus trips are based on the same time and day-of-the-week as the survey. The travel time for bus, car and taxi are adjusted based on the traffic congestion condition on the day of the travel, relative to that on the day of API query.

Figure A8: Sample Routes

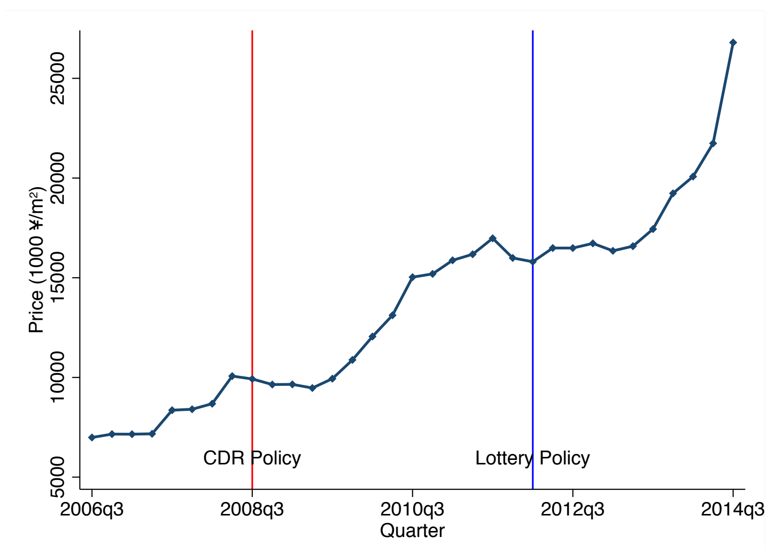
Note: The figure shows travel time and cost of six routes for a particular trip that started from 7:09am on 9/12/2010. The chosen mode was subway.

Figure A9: Housing Transaction Data

(a) Sample Location

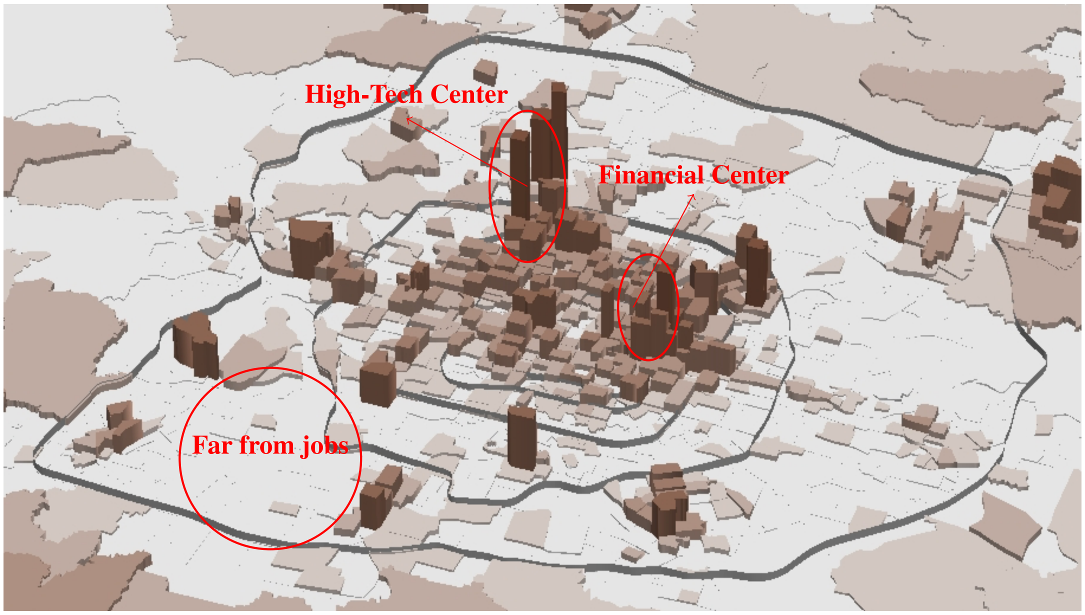


(b) Housing Price



Note: The top panel shows the property locations in the mortgage data overlay with ring roads, subway lines (as of 2015), government-designated key schools (65), and government-designated parks. The bottom panel shows quarterly average prices weighted by the size of the housing unit deflated to 2007 price level. The CDR policy denotes the driving restriction policy while the lottery policy denotes the vehicle purchase restriction through lotteries.

Figure A10: Job Density



Note: Job density by TAZ based on the work location from the mortgage data.

Figure A11: Neighborhood (Jiedao) and Housing Data

Note: Figure illustrates the configuration of neighborhoods (i.e., Jiedaos) relative to housing units, ring roads, and subway lines in the southwest section of central Beijing, between the second and third ring roads.

Figure A12: Event Study of the Price Gradient Estimates

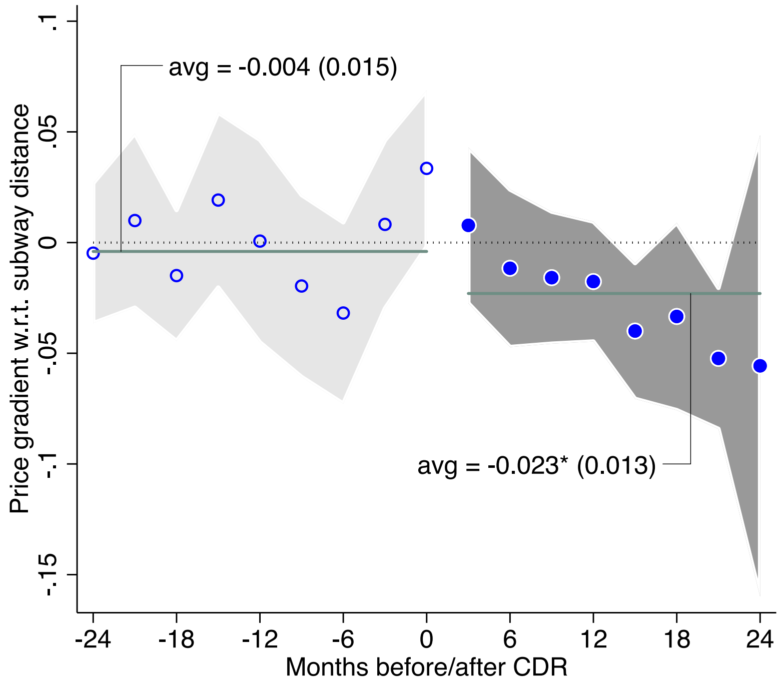


Figure A13: Falsification Test on Price Gradient

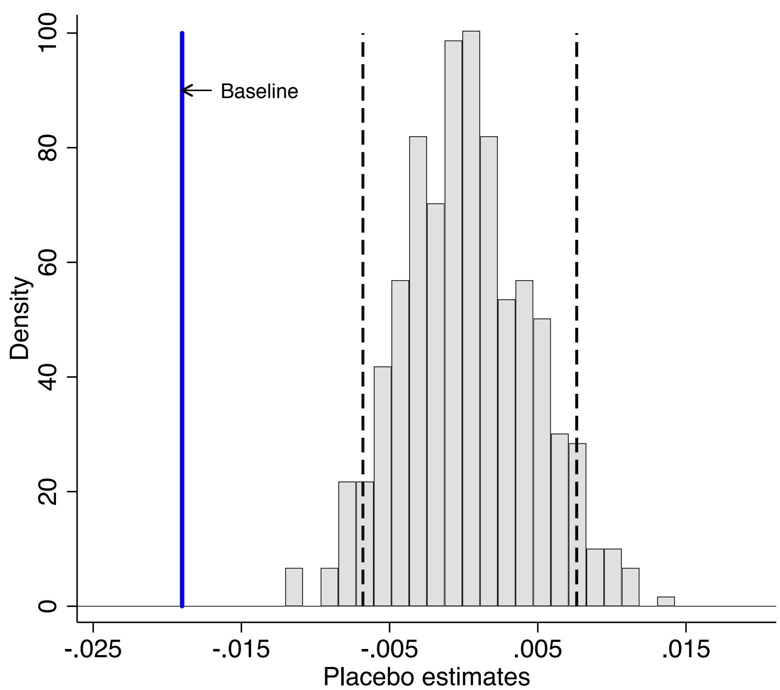
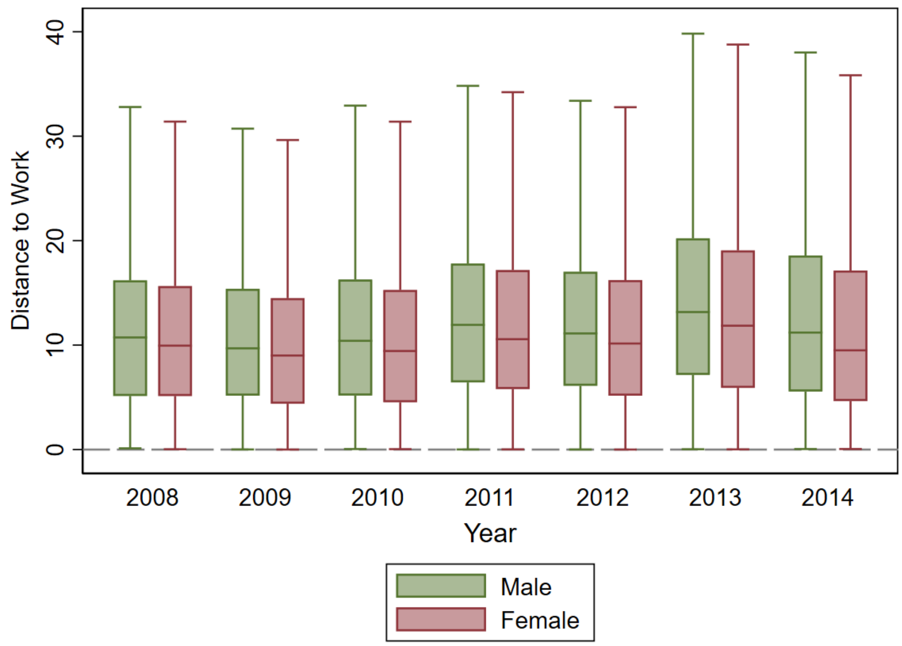
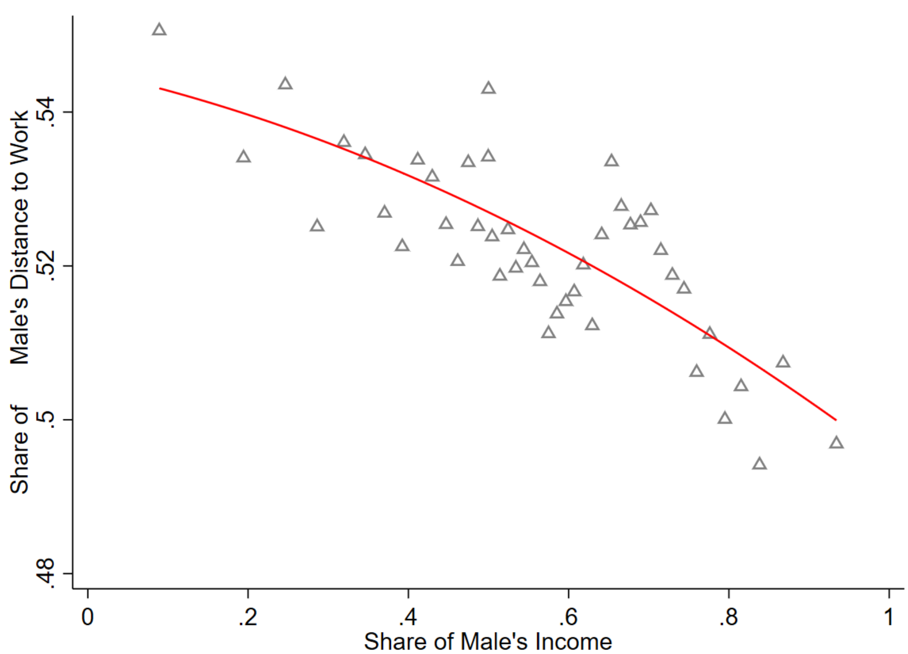


Figure A14: Distance to Work

(a) Distance to Work for By Gender



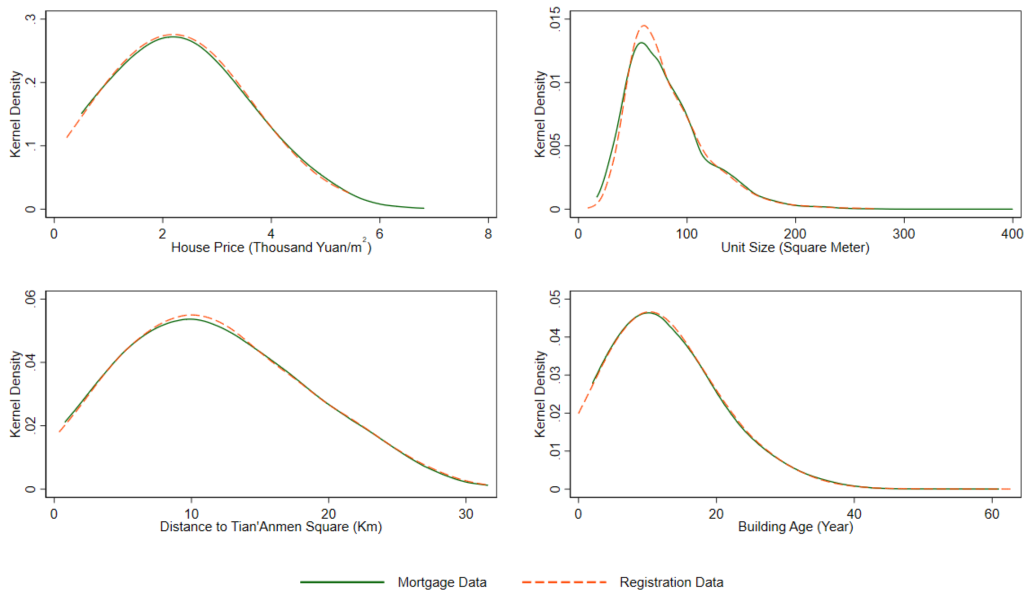
(b) Borrower's Share of Distance to Work with respect to Borrower's Share of Income



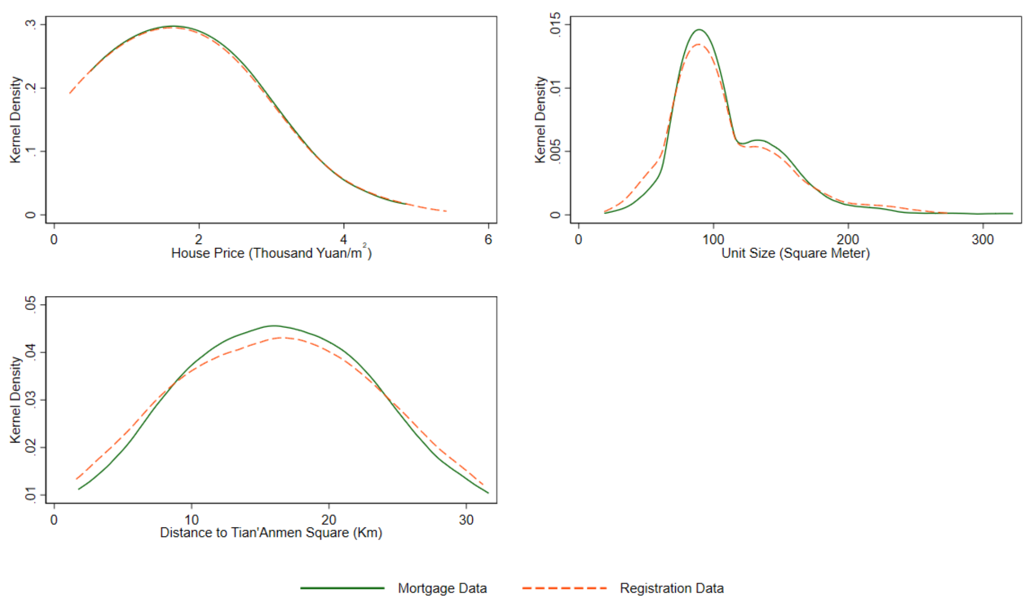
Note: Panel (a) shows how the boxplots of the distance to work by year for male and female members, separately. The bar in the middle of the box is the median and the interquartile range is shown by the box. The green boxplots are for males while the red boxplots are for females. Male borrowers have a longer commute than female borrowers. The distance has increased over time reflecting the expansion of the city and transportation infrastructure. Panel (b) is the binned scatter plot showing that the male member's relative income share has a weak negative relationship with his share of distance to work (the male member's distance to work over household's total distance to work).

Figure A15: Comparing Mortgage and Real Estate Listings after Weighting

(a) Resales

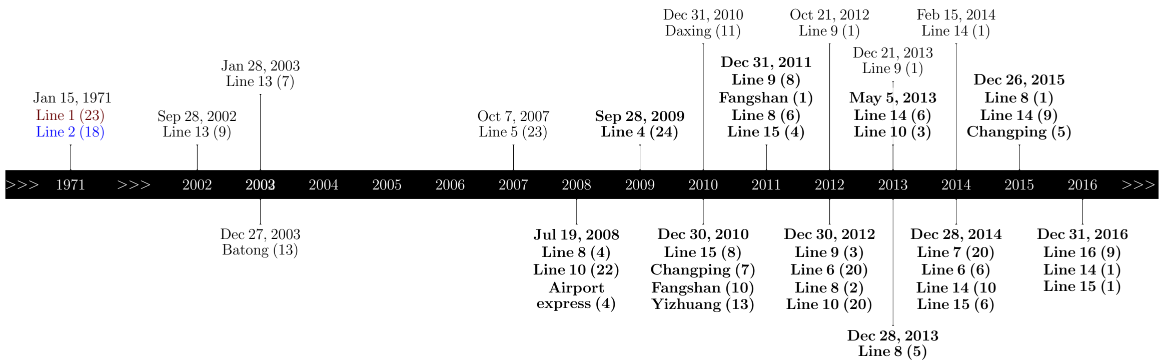


(b) New Properties



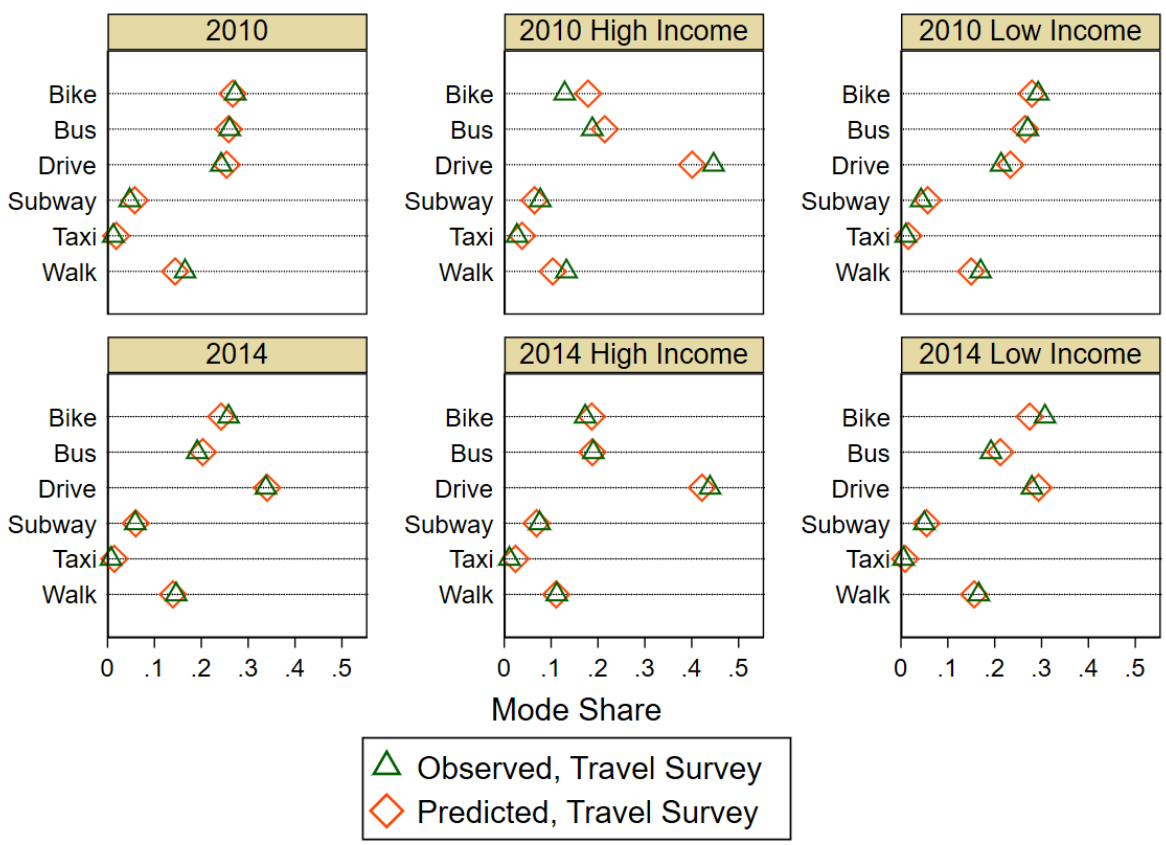
Note: The graphs gauge the representativeness of the mortgage data by comparing properties in the re-weighted mortgage data set with properties in a much larger real estate listing database in terms of prices per square meter, property size, property age, and distance to Tian'anmen Square. The upper panel shows comparisons of resales (58,718 obs in mortgage dataset and 160,836 obs in real estate listings) and the bottom panel shows comparisons of new sales (18,529 obs in mortgage dataset and 309,256 in real estate listings). Solid lines represent the mortgage dats and dashed lines represent real estate listings. As shown in the figure, after the weighting, properties in these two data sets are well balanced.

Figure A16: Beijing Subway Expansion Timeline



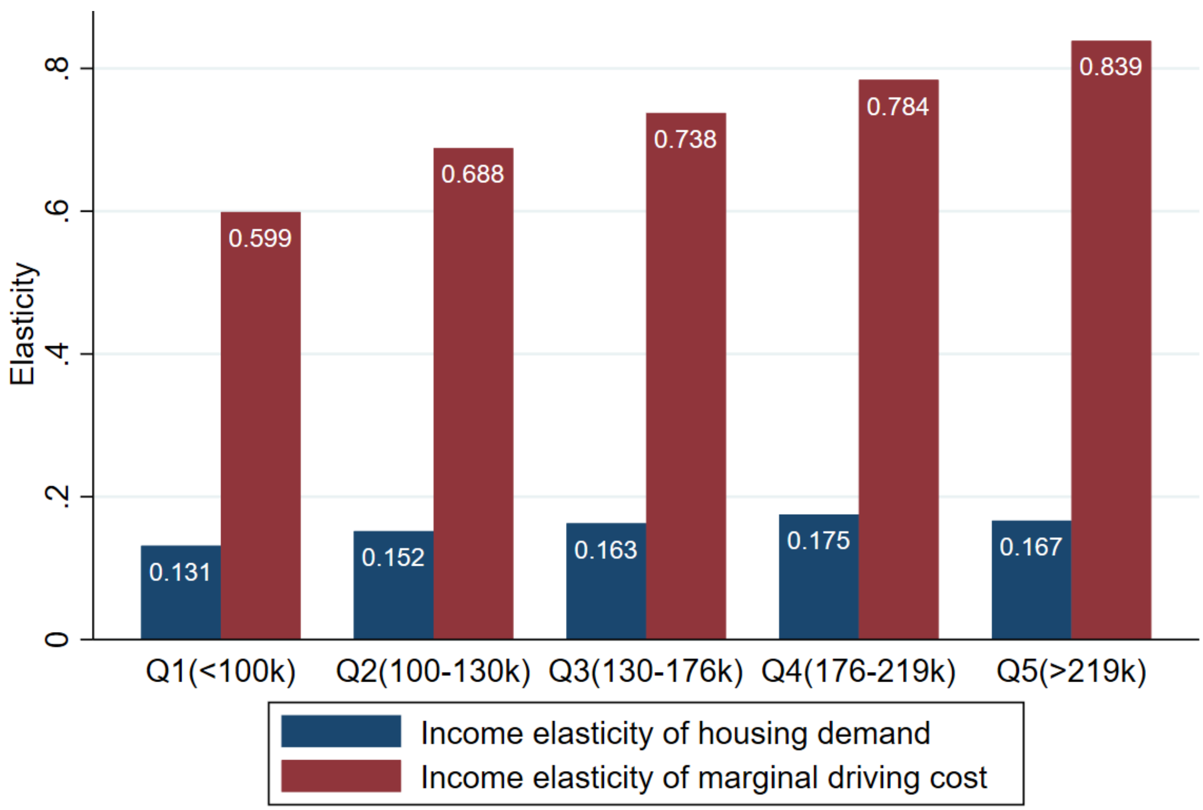
Note: the figure shows the timeline of subway expansion. The number of new subway stations for each expansion (either a new line or an extension of existing line) is shown in the parentheses. From 2007-2016, 14 new subway lines and one airport expressway were constructed with a total length of 468 kilometers and 275 new subway stations opened, making the Beijing subway system not only the most rapidly expanded but also the second longest in the world.

Figure A17: Model Fit: Travel Mode Choices



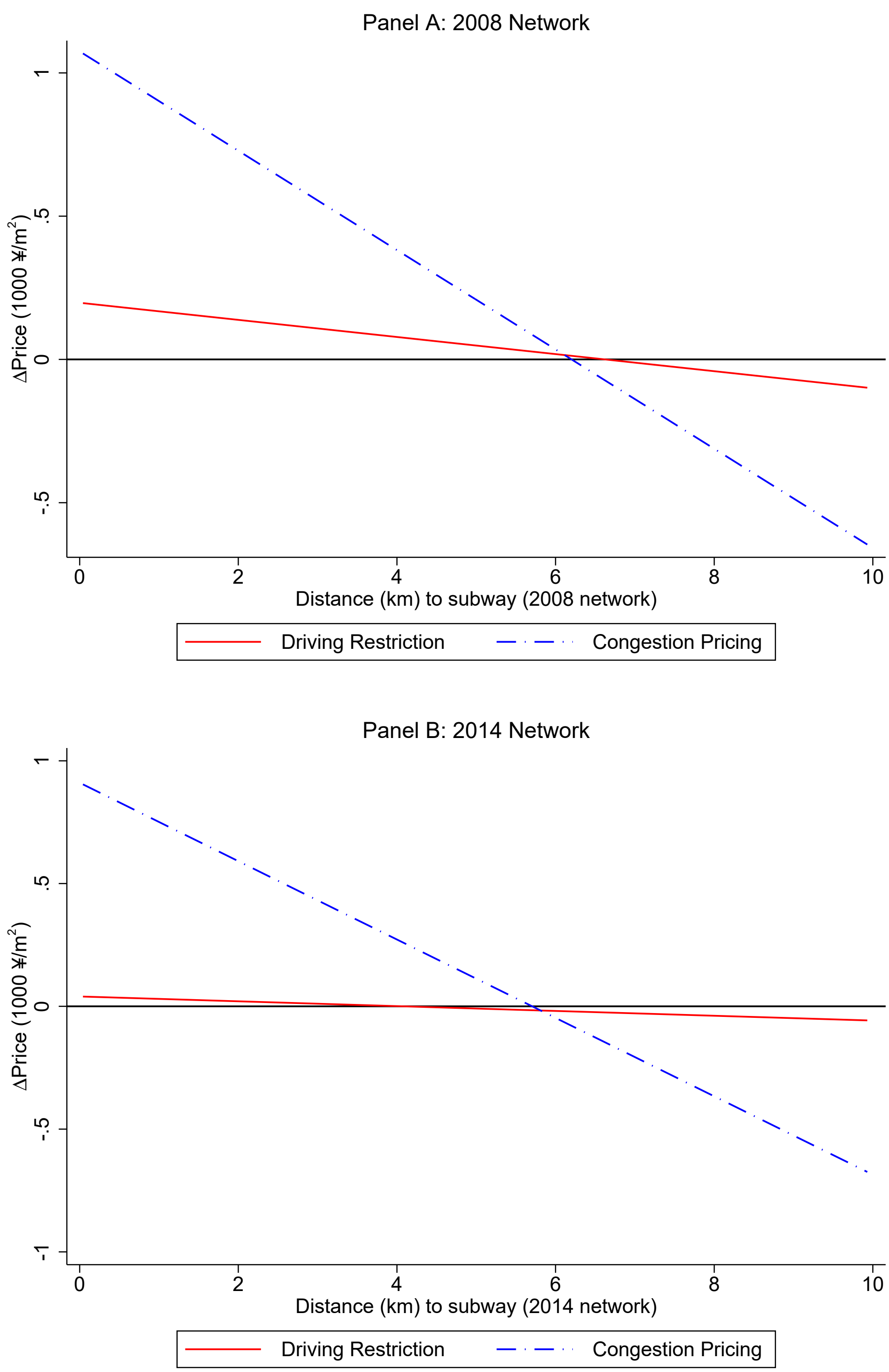
Note: This figure gauges the fit of our empirical model. The triangles show observed shares of different travel modes in the 2010 and 2014 travel survey data. The diamonds represent (in-sample) model predictions of travel mode shares based on travel survey data. Our model fits the observed mode share well for both income groups.

Figure A18: Income elasticity of housing demand/marginal driving cost



Note: This figure shows implied income elasticity of housing demand (i.e., size) and income elasticity of marginal driving cost by household income quintiles using 2014 mortgage data.

Figure A19: Change in Price Relative to the Baseline



Note: The plot shows the changes in the price gradient (with respect to subway distance) as a result of driving restriction and congestion pricing relative to the price gradient under the no policy scenario. The top graph is under the 2008 subway network and the bottom graph is under 2014 network.

Table A1: Effect of CDR on Price Gradient w.r.t. Subway Proximity

	(1)	(2)	(3)	(4)	(5)	(6)
ln(Subway Distance)	-0.111***	-0.005	-0.004	-0.000	-0.001	0.003
	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.017)
ln(Subway Distance) $\times$ CDR	-0.002	-0.018*	-0.019**	-0.023*	-0.019**	-0.023*
	(0.013)	(0.009)	(0.009)	(0.013)	(0.009)	(0.013)
ln(Subway Density)					0.004	0.007
					(0.007)	(0.008)
YearxMonth FE	Y	Y	Y	Y	Y	Y
neighborhood FE	N	Y	Y	Y	Y	Y
Complex-level Controls	N	N	Y	Y	Y	Y
Weighted	N	N	N	Y	N	Y
Observations	9640	9634	9634	9634	9634	9634
Adjusted R^2	0.236	0.522	0.534	0.688	0.534	0.688

Note: Sample spans 24 months before and after the car driving restriction policy (CDR). The dependent variable is log(price per m^2). Subway distance is the distance (in km) from the housing unit to the nearest subway station. Subway density is constructed at the TAZ level as the inverse distance weighted number of subway stations from the centroid of an TAZ. Standard errors clustered at the neighborhood level are in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Weights are constructed based on a data set of housing translations which accounted for about 17% of total housing transactions in Beijing during 2006 to 2014.

Table A2: Effect of CDR on Household Sorting

	ln(Distance to Subway)			ln(Distance to Jobs)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Household Income)	0.041*	0.026	0.012	0.203***	0.227***	0.214***
	(0.021)	(0.020)	(0.027)	(0.039)	(0.048)	(0.044)
Ln(Household Income)$\times$ CDR	-0.039*	-0.041*	-0.017	-0.122***	-0.109**	-0.125***
	(0.024)	(0.023)	(0.027)	(0.042)	(0.042)	(0.046)
YearxMonth FE	Y	Y	Y	Y	Y	Y
neighborhood FE	Y	Y	Y	Y	Y	Y
Complex-level Controls	N	Y	Y	N	Y	Y
Household Demographics	N	Y	Y	N	Y	Y
Weighted	N	N	Y	N	N	Y
Observations	9634	9634	9634	9634	9634	9634
Adjusted R^2	0.833	0.837	0.790	0.229	0.254	0.213

Note: Sample spans 24 months before and after CDR. Standard errors clustered at the neighborhood level are in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Weights are constructed based on a data set of housing translations which accounted for about 17% of total housing transactions in Beijing during 2006 to 2014.

Table A3: The Elasticity of Speed w.r.t. Traffic Density

	(1)	(2)	(3)	(4)	(5)	(6)
ln(density)	0.032	-0.173***	-0.683***	-1.018***	-1.099***	-0.620***
	(0.026)	(0.037)	(0.076)	(0.066)	(0.089)	(0.030)
Observations	393,634	386,717	412,556	243,302	156,670	1,592,879
Density (cars/lane-km)	< 8	≥ 8 & < 14	≥ 14 & < 23	≥ 23 & < 35	≥ 35	All
Average speed (km/h)	65.3	70.9	63.8	50.0	30.3	60.5

Note: Each column reports results from a 2SLS regression where the dependent variable is ln(speed in km/h) and the key explanatory variable is log(traffic density in the number of cars/lane-km). The unit of observation is road segment by hour during peak hours within 6th ring roads in 2014. The first five columns are based on the observations in each of the quintiles: column (1) is for observations in the first quintile of the density distribution, and column (5) is for observations in the fifth quintile. The last column is for all observations. The IVs are constructed based on the driving restriction policy which has a preset rotation schedule for restricting certain vehicles from driving one day per week based on the last digit of the license plate number. We construct a policy indicator being 1 for the days when vehicles with a license number ending 4 or 9 are restricted from driving. We interact this variable with ring road and hour-of-day dummies. The control variables include temperature (C^o), wind speed (km/h), visibility (km), dummies for (16) wind directions, and dummies for (5) sky coverage at the hourly level. See Yang et al. (2019) for details on data construction and the variables. The time fixed effects include day-of-week, month-of-year, hour-of-day, holiday fixed effects. The spatial fixed effects include road segments (or monitoring stations) fixed effects, and the interactions between ring road dummies (e.g., inside 2nd ring roads, between 2nd and 3rd ring roads) with hour-of-day (Ring roads $\times$Hour). Parentheses contain standard errors clustered by road segments. Significance: *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$.

Table A4: Sorting Model Estimates Without EV- Second Stage

Variables	OLS	OLS	IV1	IV1+IV2	IV3	All
	(1)	(2)	(3)	(4)	(5)	(6)
Price (in 1 million RMB)	-2.073***	-2.062***	-4.224***	-5.031***	-7.101***	-5.356***
	(0.180)	(0.176)	(0.535)	(0.432)	(1.646)	(0.418)
Ln(property size)	-3.590***	-3.657***	0.104	1.512**	5.102*	2.079***
	(0.248)	(0.251)	(0.932)	(0.761)	(2.937)	(0.765)
Building age	-0.032***	-0.026***	-0.076***	-0.095***	-0.144***	-0.103***
	(0.006)	(0.006)	(0.012)	(0.010)	(0.040)	(0.010)
Complex FAR	0.017	0.001	-0.007	-0.009	-0.009	-0.009
	(0.031)	(0.023)	(0.021)	(0.025)	(0.036)	(0.027)
Ln(dist. to park)	0.167***	0.052	-0.196***	-0.285***	-0.513**	-0.321***
	(0.059)	(0.054)	(0.073)	(0.075)	(0.225)	(0.081)
Ln(dist. to key school)	0.631***	0.555***	0.312***	0.223**	-0.034	0.187**
	(0.060)	(0.091)	(0.086)	(0.089)	(0.213)	(0.091)
Year-Month-District FE	Y	Y	Y	Y	Y	Y
Neighborhood FE		Y	Y	Y	Y	Y
First-stage F			10.48	14.22	9.88	14.22
J Statistics			7.62	8.30		15.75
P value: overidentification test						0.01
Avg. Price elasticity	3.09	3.10	0.94	0.13	-1.94	-0.19

Note: The number of observations is 79,894. The dependent variable is the mean utilities recovered from the first stage (without including EV in the first stage). The first two columns are from OLS and the last four are from IVs. Complex density is measured by the floor-area ratio of the complex, the size of the total floor area over the size of the parcel that the complex is located on. Distance to key school is the distance to the nearest key elementary school. Column (3) and (4) use IV1 as price instruments, i.e. the average attributes of properties (building size, age, log distance to park, and log distance to key school) that are within 3km outside the same complex sold in a two-month time window from a given property. Column (4) and (6) additionally use IV2, i.e. the interaction between the distance related instruments defined in Column (3) and the winning odds of the vehicle licence lottery as instruments. The winning odds decreased from 9.4% in Jan. 2011 to 0.7% by the end of 2014. Column (5) uses number of houses transacted in the three-month time window in the real estate listings dataset. Standard errors clustered at the neighborhood-year level are in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Model Fit: Effect of CDR on Price Gradient

	(1)	(2)	(3)
ln(Subway Distance)	-0.175***	0.011	
	(0.015)	(0.036)	
ln(Subway Distance) × CDR	-0.010***	-0.010***	-0.010***
	(0.002)	(0.002)	(0.002)
Neighborhood FE	N	Y	N
Property FE	N	N	Y
Adjusted R^2	0.329	0.400	0.999

Note: The analysis is based on the properties sold in 2014 in the mortgage data with 7,136 observations. We simulate the equilibrium prices under the 2008 network for two scenarios: with and without the car driving restriction (CDR). We then estimate regressions as in Table A1. The dependent variable is log(price per m^2). Subway distance is the observed distance (in km) from the housing unit to the nearest subway station (based on 2008 network). Standard errors clustered at the neighborhood level are in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The driving restriction steepens the price gradient with respect to subway access consistent with the result in Table A1 based on the observed data.

Table A6: Simulation Results: with Sorting and Housing-Supply Response

	2008 Subway Network						2014 Subway Network					
	(1) No Policy		(2) Driving restriction		(3) Congestion pricing		(4) No Policy		(5) Driving restriction		(6) Congestion pricing	
	Baseline levels		Δs from (1)		Δs from (1)		Δs from (1)		Δs from (1)		Δs from (1)	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Panel A: travel outcomes												
Drive	40.87	23.79	-5.93	-3.33	-2.72	-4.34	-1.95	-1.61	-7.61	-4.77	-4.67	-5.58
Subway	10.24	13.49	1.18	0.59	1.03	1.04	4.89	5.91	6.39	6.68	5.96	6.76
Bus	22.73	29.45	2.15	1.36	0.45	1.45	-1.50	-2.21	0.44	-0.94	-0.89	-0.64
Bike	17.10	22.91	0.72	0.36	0.43	0.87	-0.57	-0.83	0.15	-0.46	-0.13	0.07
Taxi	1.80	0.86	0.80	0.28	0.43	0.25	-0.41	-0.35	0.22	-0.12	-0.09	-0.17
Walk	7.26	9.51	1.08	0.74	0.38	0.72	-0.45	-0.91	0.42	-0.38	-0.17	-0.44
Speed	20.69		3.52		3.72		1.11		4.48		4.75	
Panel B: housing market outcomes												
Borrower's Distance to work (km)	19.45	18.88	0.03	0.04	-0.48	-0.29	0.51	0.53	0.60	0.59	0.01	0.25
Co-Borrower's Distance to work (km)	17.86	12.21	0.02	0.03	-0.40	-0.21	0.51	0.52	0.59	0.56	0.08	0.31
Distance to subway (km)	5.77	4.67	-0.04	0.02	-0.16	-0.08	-4.57	-3.82	-4.57	-3.81	-4.58	-3.82
Panel C: welfare analysis per household (mil. ¥)												
Consumer surplus			-238.9	-55.3	-126.1	-93.2	105.8	75.8	-130.1	20.5	-18.8	-12.7
Subway cost							95.3	95.3	95.3	95.3	95.3	95.3
Toll revenue					143.3	143.3					136.2	136.2
Net welfare			-238.9	-55.3	17.2	50.1	10.5	-19.5	-225.4	-74.8	22.1	28.2

Note: Simulated results based on estimated model parameters using 2014 housing data. We allow housing supply to adjust with a price elasticity of two (implying that a ¥1,000 price increase would induces a 0.12% increase in housing supply on average). Column (1) shows the baseline results while columns (2) to (6) show the differences from column (1). The driving restriction prohibits driving in one of five work days. Congestion pricing is ¥1.43 per km to generate the same reduction as the driving restriction. High-income household are those with income above the median household income. Subway cost per household includes the construction cost and the 30-year operating cost equally shared among 7.2 million households. We apportion 75% it to work commute in our welfare analysis. Toll revenue is the revenue per household from congestion pricing during a 30-year period (to keep a balanced government budget, the toll revenue is recycled uniformly to each household). Net welfare is consumer welfare per household after revenue recycling or tax-funded subway construction and operation.