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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 diaries and housing transactions with home and work locations in Beijing, we jointly estimate travel mode and residential location decisions. The estimation highlights the importance of incorporating work commute in housing decisions and features preference heterogeneity for the ease of work commute by gender. 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 work. 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 when combined deliver the largest congestion relief and efficiency gain and at the same time achieve self-financing, with revenue from congestion pricing fully covering the cost of subway expansion.

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A data appendix is available at http://www.nber.org/data-appendix/w29012

1 Introduction

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 the urban spatial structure through residential location adjustment, 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. It has adopted a driving restriction policy since 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 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 primary channels by which these policies affect travel mode and residential location choices, we proceed in several steps. We first develop a stylized theoretical model based on LeRoy and Sonstelie (1983) and

[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.`

Brueckner (2007) while accounting for endogenous congestion and heterogeneity in income and commuting technologies. The model illustrates differential impacts of urban transportation policies on the spatial pattern of residential locations and highlights countervailing forces at play between travel mode choices and housing location. It also suggests that 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 leverages fine spatial resolutions from two unique data sets that allow us to jointly model the residential locations and commuting choices. 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 home location information but also work 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.

We then 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 (separately for each working household member). We allow the 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 travel mode choices, household locations, the congestion level and housing prices.

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 and the time and pecuniary cost information of all hypothetical commuting trips that we construct. We utilize the estimated parameters from this step to construct a measure on the work-commute attractiveness for each home and each buyer in our mortgage dataset, which we call the "ease-of-commuting" attribute of a housing choice. 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. For a given home and a potential buyer, the ease-of-commuting attribute corresponds to the expected maximum utility of commuting from home to the buyer's work location via available travel modes. It accounts for preference heterogeneity and takes into consideration upgrades in the transportation system at the time of home purchase. For married couples with two jobs, we include a separate attribute for each spouse, allowing for preference heterogeneity on the work commute by gender.

The second step recovers preference for housing attributes in a housing demand model. The ease-of-commuting index is included as an observed (buyer-specific) home attribute. The key identification challenge in the housing demand model is the potential correlation between unobserved housing attributes and housing price as well as the ease-of-commuting index. The latter two variables are equilibrium outcomes determined by observed and unobserved housing attributes. To address this challenge, we construct three sets of instrumental variables in the spirit of Berry et al. (1995) and Bayer et al. (2007): average housing and neighborhood attributes of homes at a reasonable distance from a given home, the number of homes sold in a three-month window around the sale date, and the time-varying odds of winning a license lottery to purchase a vehicle. The lottery's time-varying winning odds is a powerful IV and shifts demand for houses in premium locations (close to subways and the city center). We allow both observed and unobserved preference heterogeneity, control for home fixed effect, and estimate parameters through maximum-likelihood estimation with a nested contraction mapping that is combined with IVs (Train and Winston, 2007).

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 2008 to 2014, and congestion pricing. Since the first two policies have been enacted, we begin with a no-policy counterfactual and then compare this no-policy baseline to each policy as well as their combinations. We also compare partial equilibrium outcomes that do not allow residential sorting to a general equilibrium that allows households to relocate in response to the transportation policy. Our simulations also account for 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 homes near the 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 gains as households are incentivized to live closer to work locations and drive less. On the other hand, sorting in response to subway expansion would lead to a larger separation between housing and work locations, damping the congestion reduction effect and welfare gains 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 either 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, congestion pricing is regressive and leads to a larger 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 adjustment margins 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. As the urban literature has long pointed to "wasteful commuting" that results in equilibrium housing and transportation choices deviating from the 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.

Second, our analysis contributes to a large equilibrium residential sorting literature by incorporating endogenous work commuting decisions in 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 that address economic, social and environmental challenges (Epple and Sieg, 1999; Kuminoff et al., 2013).[2] Most existing papers use the distance to work to measure ease-of-commuting and treat it as an exogenous attribute, even though ease-of-commuting is endogenously determined by both residential locations and equilibrium traffic congestion. Our approach is perhaps closest to Kuminoff (2012) which allows for households to make decisions in both the work and housing markets 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 to our knowledge the first in the empirical sorting literature that explicitly models congestion as an equilibrium outcome that is simultaneously determined by household locations and travel mode choices.

Third, our paper relates to the literature on transportation policies that address the negative congestion externality (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 the underlying travel and housing choices, our equilibrium sorting framework provides a micro-foundation for the reduced-form impact evaluation studies. More importantly, the unified framework offers a common yardstick to evaluate actual and counterfactual policies over a wide 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) that 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 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 analysis. Section 4 lays out the equilibrium sorting model and the estimation strategy. Estimation results are presented 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 (Almagro and 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 motivate our setup with a graphical presentation of the welfare effects of two transportation policies that are 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 homes 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 A, 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 A.

[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 Policy Background, Data Description and Reduced-form Evidence

3.1 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 vehicles grew from 0.7 million units in 2001 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 grew from about \$1,500 to nearly \$9,000 per year, and the vehicle stock increased from one million to over six million.[13]

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, a vehicle purchase restriction, and a massive subway and rail transportation infrastructure investment boom. The driving restriction 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.[14] In an attempt to

[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.

[13] 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, compared to 0.46 in New York city and 1.16 in the U.S. based on the 2010 U.S. Census.

[14] 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

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 were 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 became increasingly difficult: the winning odds decreased from 1:10 in early 2012 to nearly 1:2000 in 2018 as the pool of lottery participants increased dramatically while the number of licenses fell over time (Xiao et al., 2017; Li, 2018; Liu et al., 2020). Along with demand-side strategies, the Beijing municipal government also invested heavily in public transportation infrastructure. From 2007 to 2018, 16 new subway lines were built with a combined length of over 500km (See Appendix Figure A1 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.[15]

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. From a neoclassical microeconomic perspective, the aforementioned policies fail to directly 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.[16] 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).

3.2 Data Description

To compare the impacts of different transportation policies on 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 home buyers.

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including Bogotá, Mexico City and New Delhi. The impacts of these policies on reducing congestion and air pollution have been mixed (Davis, 2008; Viard and Fu, 2015; Carrillo et al., 2016; Zhang et al., 2017).

[15] 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. One intended effect of these expansions is to slow the growth of personal vehicle use by making public transportation more accessible. See Anderson (2014); Yang et al. (2018); Gu et al. (2020) for recent analysis on the impact of subway expansion on traffic congestion.

[16] 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, potentially as soon as late 2021.

Beijing Household Travel Survey We utilize two rounds of the Beijing Household Travel Survey (BHTS) that are collected in 2010 and 2014 by the Beijing Transportation Research Center (BTRC), an agency of the Beijing municipal government. The survey is designed to inform transportation policies and urban planing. It 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 time, the trip purpose and mode used.

Our analysis focuses on 73,154 work commuting trips (home to work and work to home). Work trips are likely to be the most important trips in housing purchase decisions. They account for 53% and 59% of weekday trips among the working-age respondents and 62% and 75% of total travel distances in 2010 and 2014, respectively.

Table 1 provides summary statistics for variables used in the analysis by the survey year. Household income increased dramatically from 2010 to 2014, with the share of the lowest income group ($<$ 50k annually) decreasing from 48 to 18 percent while shares for higher income groups grew. Vehicle ownership increased from 44 to 62 percent. Both the share of respondents living within the 4th ring road (which proxies for the city center) 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 work locations. Other individual attributes (gender, age, and education) are similar across the two years.

To understand a commuter's travel mode choices, we need attributes for all travel modes in his choice set. We focus on six travel modes: *Walk*, *Bike*, *Bus*, *Subway*, *Car*, and *Taxi*, as other modes (motorcycles, company shuttles, and unlicensed taxis) collectively account for less than 4% of all trips. The travel survey only reports the actual mode that is taken. We complement the travel survey and construct commuting time, distance, and cost for each of the six modes and validate our calculations using information from reported trips.

Appendix Figures A3 and A4 provide two illustrations. We use Baidu Map API to calculate the travel time and distance for walking, biking, car and taxi. Baidu maps incorporate predicted congestion level based on the time of day and day of week. We query Baidu API at the same departure time that is recorded in the travel survey (e.g., 7am). To account for changes in the average congestion level between the survey year and the year we queried Baidu API, we adjust the predicted travel time based on the annual traffic congestion index across different regions in Beijing. For bus travel time, we use Gaode Map API as Baidu does not provide information on the number of transfers and walking time between bus stops, which can be substantial for longer trips. To take into account the subway expansion in our sample period, we use historical subway maps and an GIS software to reconstruct the historical subway network. The subway travel time is calculated based on the published time schedules of subway lines. Our calculation assumes that commuters use the subway stations that are closest to their trip origin and destination and incorporates the walking distance to the subway stations as well as the corresponding time in the total trip distance and duration. Appendix **??** provides more details on the full procedure.

Figure 3 plots each travel mode's observed share of commuting trips, as well as the *constructed* travel time, cost, and distance by each mode. Panel (a) contrasts travel patterns in 2010 with those in 2014 and presents several notable patterns. First, walking account for a significant share of all commuting trips: 15.0% and 13.5% in 2010 and 2014, respectively. These trips take 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 see a reduction while the share of car (i.e., driving) and subway have increased, reflecting the increase in vehicle ownership and the expansion of the subway network. Third, walking and subway trips are the longest in duration, while the subway and car trips are longest in distance. While car trips have slightly longer duration and distance than taxi trips, they are cheaper. Overall, the trade-off 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, take taxis and less likely to use other modes, compared with low-income households. As a percentage of the 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 housing data below that display no evidence on strong income-delineated residential sorting patterns.

Housing Transactions Data Data on housing transactions come from a major government-sponsored mortgage program in Beijing from July 2006 to July 2014. As is reflective of the housing supply in urban China, almost all of the housing units are within housing complexes analogous to condominiums in the United States. The interest rate for this mortgage program is subsidized and more than 30% lower than the commercial mortgage rates for eligible borrowers. Virtually all home buyers apply for mortgages through this program first before going to other loans. There are no refinancing activities and each mortgage contract represents a housing transaction.

The final data set includes 79,884 mortgage transactions. Table 2 provides summary statistics of the data.[17] The mortgage data include information on household demographics including income, age, marital status, residency status (*hukou*), and critically for our analysis, the work address for the primary borrower (and that of the co-borrower if present). The data also contain information on housing attributes such as the size, home age, street address, transaction price, and date when the mortgage was signed. We geocode the home and work locations. The mortgage data represent a subset of housing transactions and may be subject to selection issues. Hence, we re-weight the mortgage data to match the population distribution of housing price, size, age, and distance to city center using entropy balancing (Hainmueller, 2012). Appendix B.2 discusses the re-weight procedure in more detail and additional data patterns (such as differences in commuting distance by gender). We use the weighted sample in our benchmark analysis and the unweighted sample in robustness

[17] 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.

checks.

Appendix Figures A5 maps the location of all home transactions in the mortgage data overlaid with black ring roads and blue subway lines (as of 2015). Beijing's spatial structure largely represents a monocentric city possessing multiple ring roads, with some notable exceptions. The expanding set of concentric ring roads layouts the city center. For example, the 2nd ring road largely traces out the contour of the old Beijing prior to the 1980s. On the other hand, there are several large work clusters across the city, such as the financial cluster between the 2nd and 4th ring roads on the east side of the city and a high-tech cluster towards the northwest between the 3rd and 5th ring roads. Government-designated signature schools are denoted by red stars and the government designated parks by green areas, which are important amenities that affect housing purchase decisions.[18] Signature schools are concentrated within the 4th ring road while the parks are more dispersed across the city. Beijing has a total of 18 districts, each containing on average 8 Jiedaos (or neighborhoods).

Figure 4 shows the spatial pattern of housing and household attributes by Traffic Analysis Zone (TAZs) based on the mortgage transactions from 2006 and 2014, with a warmer color representing a higher value. TAZs are spatial units defined by the government used for Beijing transportation planning purposes. They are one to two square kilometers on average and smaller when they are closer to the center of Beijing. There are 2050 TAZs in 2014. Housing prices tend to be higher in the city center while housing size smaller, as predicted by the classical monocentric city models. Distance to work is shorter for those living close to the city center, reflecting a higher concentration of work closer to the city center. There are exceptions: some TAZs in the northwest outside the 5th ring road exhibit short work distance, due to a high-tech center in that area as shown in Figure A6. Relative to housing price, housing size, and commuting distance, the pattern of household income is more mixed. Some high-income households opt to live in larger homes with a lower unit price to the north of the city center, reflecting the classic distance-housing size tradeoff illustrated in the monocentric city model in Section 2. In addition, the northern parts of the city attract high-income households with better amenities and more work opportunities (Appendix Figures A5 and A6).

To incorporate commuting into housing decisions, we need to construct work commute attributes (i.e., time and out-of-pocket costs). In theory, one could construct the attributes of different travel modes for each potential housing choice for a given home buyer/work location as illustrated in Appendix Figure A3. However, this is technically infeasible given the vast number of home-work-mode pairs and the query restrictions by the Baidu and Gaode APIs. The large 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 home and a one percent sample of homes randomly chosen from those sold during a two-month

[18]There are 65 signature schools in Beijing that are designated by the Beijing municipal government as the 'key' elementary schools. 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.

window (30 days before and after) around the purchase date. Beijing's real estate market was fluid during our data period: the median days-on-market for a home seller is only 8 and 13 in 2013 and 2014, respectively, with the average days on market 22 and 38 days. For each home in a household's choice set, we construct the travel mode attributes for both the male borrower's and the female borrower's work commute, based on their respective work locations. The construction of the mode attributes involves over 13 million route-mode combinations.

3.3 Reduced-form Evidence

Before proceeding to the structural sorting model, we examine whether changes in the transportation system are capitalized into housing prices and the residential sorting in response to these changes is meaningful. Specifically, we examine the housing market response to the car driving restriction policy (CDR). The CDR was implemented in July 2008 and prohibited car-owners from driving one day a week based on the last digit of their license plates. The theoretical model in Section 2 predicts both an adjustment in travel choices (substitution away from driving towards the public transportation) and relocation of residential locations. Driving restrictions induce greater demand for homes closer to the public transportation, increasing the price of these homes. In addition, wealthier households with potentially higher values of time are more likely to sort into these units, the so-called transit-induced gentrification.

Figure 5 shows scatter plots of home prices in ¥1,000$/m^2$ against the distance to the nearest subway station before and after the CDR.[19] The top panel uses raw data, while the bottom panel shows residualized plots after controlling for year-by-month and neighborhood fixed effects.[20] The price gradient becomes steeper post CDR, suggesting that homes close to subways command a higher price premium after the policy. Consistent with theoretical predictions, the driving restriction increases the price premium of the homes near subway stations. Appendix Section C provides an event study analysis, a falsification test and additional evidence.

We next examine residential sorting by regressing the distance from home to subway (and distance between home and work) on the interaction between the CDR dummy and household income (Appendix Section C. Driving restriction policy reduced the distance to the nearest subway station and distance to work much more for high income households. This provides suggestive evidence that high-income households sorted closer to premium locations and low-income households sorted away, potentially because they were priced out.

The reduced-form analyses above confirm the importance of the housing market capitalization and sorting in response to transportation policies. We now turn to an equilibrium sorting model of housing demand and commuting choice that features preference and spatial heterogeneity to quantify the channels by which

[19]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.

[20]A neighborhood is defined as a Jiedao, an administrative unit that is similar to a census tract and is 2.8 square kilometers in size on average. Each district of Beijing contains an average of 8 Jiedaos. We use Jiedao to denote neighborhoods where homes share similar observed and unobserved amenities.

transportation policies affect these choices. This allows us to analyze the efficiency and equity impacts of different policies in a unified framework.

4 Empirical Sorting Model

We now lay out an empirical equilibrium sorting model that incorporates commuting choices into housing decisions. We first describe the model and then discuss identification and estimation of model parameters.

4.1 Model Overview

Our sorting model characterizes the determinants of individual commuting choices and residential location decisions. It also specifies the joint equilibrium conditions for the traffic congestion (a key amenity in our analysis) and the housing market. On the one hand, residential locations determine households' commute distances and affect the driving demand and hence traffic congestion. On the other hand, traffic congestion in turn affects the attractiveness of a residential location and consequently the housing demand. For example, high congestion levels increase demand for premium locations (places close to subways and the city center). The equilibrium nature of our sorting model allows for counterfactual simulations and provides direct comparative statics of housing prices, residential locations, and congestion levels from marginal or non-marginal policy changes.

In practice, the choice of housing location could be part of a joint decision of work and home locations that may be simultaneous or sequential. We assume they are sequential and take work 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, employment opportunities in the same industry tend to be clustered in Beijing and switching jobs may not entail meaningful changes of work locations. Third, while the mortgage data provide rich information on locations of housing and current employment, they do not have information on job opportunities (e.g., available job openings at the time of searching). Therefore, incorporating work 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 some recent studies using the quantitative spatial models.[21]

Our approach contrasts with the emerging literature using quantitative spatial models that have made considerable advances in modeling the joint processes of work and residential locations. Improvements in the transportation system could translate into higher productivities (through better allocation of time and labor market matching), a margin of adjustment not incorporated in our model. This literature uses observed worker flows and wages to recover iceberg commuting costs via a gravity equation framework. However, with

[21] 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 it does not endogenize congestion from the transportation sector.

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. In contrast, While taking work locations as given, our equilibrium sorting framework can predict the endogenous congestion level and welfare impacts from unpriced externality across commuters under different policy scenarios.[22]

4.2 Housing Demand

We specify a characteristics-based housing demand model, in which preferences over housing are parameterized as a function of both observed and unobserved household attributes (Lancaster, 1971; McFadden, 1978; Berry et al., 1995). Our data are longitudinal, but we suppress time t to ease exposition. Conditioning on the work locations, utility for household i choosing home unit j can be written as:

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

where J is the choice set for household i and the construction of the choice set is discussed below. The household-specific price coefficient α_i is related to the log of household income y_i:

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

We use p_j to denote the price of home j, $\mathbf{x}_j$ to denote a vector of housing attributes such as size and the number of bedroom, and β_i to denote household preferences over housing attributes. The marginal utility for each housing attribute is decomposed into an individual-specific component and a population average, 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 housing attributes and ε_{ij} is an i.i.d. error term that reflects unobserved preferences over each housing choice.

Household members with commuting needs are denoted by $k \in \{Male, Female\}$. EV_{ijk} is the expected utility for member k in household i that is derived from the best commuting alternative. It characterizes the attractiveness of home j in terms of member k's work commute. This ease-of-commute term is constructed from a discrete choice model of commuting mode that we describe below. It is affected by the congestion level, which is determined in equilibrium by all households' travel mode choices and residential locations. Preference for ease-of-commute ϕ_{ik} differs across gender and households and is characterized by random

[22] One 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 because spatial mismatch and 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.

coefficients:

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

In subsequent formulations, we suppress subscript k for the ease of exposition and use EV_{ij} to denote the commuting utility for both household members $\sum_k \phi_{ik} EV_{ijk}$. The commuting utility is the key innovation relative to residential sorting models that incorporate commuting based on fixed distances. It allows for a joint consideration of the heterogeneous impact of transportation policies on commuting costs across individuals and homes.

4.3 Travel Mode

Utility-maximizing individuals within a household choose a commuting mode based on the time and financial cost associated with each of the six modes: Walk, Bike, Bus, Subway, Car, and Taxi. In this subsection, we abuse the notation and use i to denote an individual within a household rather than a household. This is consistent with the level of aggregation in the travel survey that reports the travel mode choices for each commuting member within a household.[23] Preferences vary across individuals, such as the enjoyment of driving a car, perceived "greenness" of using public transportation, or health benefits of biking and walking. We include mode-specific random coefficients to account for these considerations. Individual i's utility of commuting from home j to work using mode choice m is specified as:

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

where M_{ij} is the set of transportation modes available to individual i. We allow for a mode-specific random coefficient, θ_m, that has a normal distribution with mean μ_m and variance σ_m. The mode-specific random coefficient for walking 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 commute duration between i's work location and home j via mode m. Note that driving time $time_{ij,car}$ is affected by the congestion level, an endogenous outcome as discussed above.[24] Time preference γ_{1i} follows a chi-square distribution with three degrees of freedom and mean μ_γ. The chi-square

[23]For the purpose of our analysis we consider the mode choices of different individuals within a household as independent because of limited information on the joint decision processs. 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 home relative to another as specified in the EV term.

[24]Road congestion affects travel times for buses in addition to driving and taxi, however this effect is more complicated as it depends on the local characteristics of the roadway, the design of bus schedules, and location of bus stops. 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 over-prediction of bus mode shares from our estimates.

distribution allows all individuals to have a positive value of time. The monetary cost of the trip is denoted as $cost_{ijm}$. Individual's sensitivity to the monetary costs of commuting is assumed to decrease in income: γ_2/y_i. Finally, variable w_{ijm} captures mode-commuter specific controls (such as the driving dummy interacted with commuter's gender) and ε_{ijm} is the i.i.d. error term.

The utility function makes it straightforward to calculate the value of time (VOT), which is $\frac{\gamma_{1i}}{\gamma_2} \cdot y_i$. In this formulation, the financial burden of travel scales 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 Becker (1965)'s framework of time allocation, 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).

Expected utility from commuting, 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. Once we obtain the expected commuting utility for all commuting members within a household, we aggregate it to the household level and use it to measure house location j's ease-of-commute given individual/household i's work locations.

4.4 Market Clearing Conditions and the Sorting Equilibrium

This section defines the sorting equilibrium and the market clearing conditions for two interrelated markets in our model: the housing market and the market for driving. In the housing market, choices of individual households aggregate to the total housing demand. Housing prices adjust to equate demand and supply (housing supply is specified in Section 6.1). In the market for driving, the equilibrium driving speed and hence congestion level is jointly determined by driving demand through all individuals' travel mode choices and road capacity (the supply of the driving market). The two markets interact in two dimensions: the spatial location of households affects the distance of work commute and the travel mode, and hence the market for driving. At the same time, the level of traffic congestion that is determined in the driving market affects the attractiveness of residential locations through the 'ease of commuting' index as discussed above, and in turn the spatial distribution of households.

Commuting Mode Choice Conditional on home location j, the probability that individual/household i chooses mode m for his work commute is defined as:

$$R_{ijm}|i,j = r(\text{cost}_{ij}/y_i, \text{time}_{ij}(v_{ij}), \text{w}_{ijm}; \theta) \tag{5}$$

where cost_{ij}/y_i and $\text{time}_{ij}(v_{ij})$ denote the vector of travel cost as a share of individual i's hourly wage and the vector of travel time for each travel mode, respectively. The travel time by cars is a function of the driving speed between individual i's work location and home location j: v_{ij}, which is endegeneously determined in equilibrium.[25] Lastly, w_{ijm} captures all other individual-trip-mode specific characteristics and θ denotes all relevant parameters in travel mode choices: $\theta = \{\{\theta_m\}_m, \gamma_{1i}, \gamma_2, \eta\}$. We use $\mathbf{R} = \{R_{ijm}|i, j\}$ to denote all households' commuting mode choices.

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

$$P_{ij} = h(\mathbf{EV}_i(\mathbf{v}), \mathbf{p}, \mathbf{X}, \boldsymbol{\xi}, \mathbf{z}_i), \tag{6}$$

where $\mathbf{EV}_i(\mathbf{v})$ is a vector of the 'ease-of-commute' index for all potential home locations giving household i's work locations. It links the housing market with the commuting mode choices, whose element is defined above in equation (4). We have made it explicit that the ease-of-commute index depends on driving speed $\mathbf{v}$. The following triplet, $\mathbf{p}$, $\mathbf{X}$, and $\boldsymbol{\xi}$, denotes prices, observed housing attributes, and unobserved housing quality for all homes in household i's choice set. The last term, $\mathbf{z}_i$, represents household i's demographic attributes. We use $\mathbf{P} = \{P_{ij}\}$ to denote all households' residential choice probabilities.

The aggregation of households' choice probabilities P_{ij} gives rise to the aggregate housing demand: $D_j = \sum_i P_{ij}(\mathbf{p}, \mathbf{v}), \forall j$. Note that the aggregate housing demand depends on both housing prices $\mathbf{p}$ and driving speed $\mathbf{v}$ through the east-of-commute index. Housing market clears when the aggregate demand is equal to aggregate supply (that also depends on housing price):

$$D_j = \sum_i P_{ij}(\mathbf{p}, \mathbf{v}) = S_j, \forall j \tag{7}$$

Driving Speed Demand for driving is determined by both housing locations and travel mode choices. Intuitively, mode choices determines the extensive margin of the driving demand (to drive or not), while housing choices determines the intensive margin of the driving demand (the commuting distance). Total driving demand and hence traffic density is the aggregation of all households' location and commuting decisions, which ultimately depends on the housing price $\mathbf{p}$ and driving speed $\mathbf{v}$:

$$D^v = \sum_i \sum_j R_{ij,car} \cdot \mathrm{dist}_{ij,car} \cdot P_{ij} = g(\mathbf{p}, \mathbf{v}). \tag{8}$$

where $R_{ij,car}$ is the driving probability for household i living in location j, $\mathrm{dist}_{ij,car}$ is the commuting distance, and P_{ij} is the probability that household i chooses location j.

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

For a fixed road capacity, the driving speed $\mathbf{v}$ decreases in traffic density:[26]

$$\mathbf{v} = f(S^v)$$

Intuitively, to sustain a higher travel speed, a transportation system has to limit the traffic density to a greater extent. Traffic market clears when the aggregate traffic demand equals to traffic supply:

$$D^v = g(\mathbf{p}, \mathbf{v}) = S^v(\mathbf{v}) \tag{9}$$

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

1. The housing market clears according to equations (6) and (7), and
2. The travel market clears according to equations (8) and (9).

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 the error terms in both the housing equation (2) and the commuting mode choice equation (3) are from continuous distributions (such as the type I extreme value distribution), then the equation system (6), and (7), (8), (9) 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 (6) and (7), conditional on a set of observed and unobserved housing attributes ($\mathbf{X}$ and $\boldsymbol{\xi}$) as well as EVs. At the same time, (8), (9) 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 $\mathbf{p}^*$. The equilibrium housing choice probabilities $\mathbf{P}^*$ and travel choice probabilities $\mathbf{R}^*$ directly follow from the sorting equilibrium.

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), and (7), (8), (9) remains a contraction mapping, and hence accommodates a unique fixed points (i.e., a unique equilibrium). 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 equilibria. A proof of existence and uniqueness is provided in Appendix D.[27]

[26]This gives rise to a congestion externality, because the driving decisions of others reduce the driving speed for household i. Figure 1 depicts the congestion externality and how the equilibrium congestion level is determined. We formulate the parametric relationship between driving speed and traffic density in Section 6.1.

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

4.5 Identification and Estimation

Choice Set We first expand on the construction of the housing choice set discussed in Section 3.2. 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 homes, 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 homes on the market 30 days before and after the sale date of the chosen home.[28] 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.

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 likely orthogonal to the realization of traffic shocks on a particular day, hence requires no instruments.

Identification & Estimation in Housing Location Choice Model In the second stage, we first construct the ease-of-commuting index EV_{ij} for every house j in household i's choice set using the logsum expression in Equation (4) and parameter estimates from travel mode choices. This step consists of a large set of EV_{ij},

[28] 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.

one for each home-work pair, including pairs between i's work location and homes that they 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 home location, following the discussion in the household travel survey and Appendix Figure A3. 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 $\widehat{EV}_{ij}$ enters the housing choice model as an observed housing attribute.

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. Following the structural demand literature we re-organize Equation (2) into a sum of household-specific utility μ_{ij} and mean utility δ_j (or alternative-specific constants) which absorbs variation from unobserved housing attributes ξ_j:

$$U_{ij} = \mu_{ij}(\theta_2) + \delta_j(\theta_1) + \varepsilon_{ij} \tag{10}$$

$$\mu_{ij}(\theta_2) = \alpha_2 ln(y_i) p_j + \sum_k X_{jk} z_{ik} \beta_k + \phi_m EV_{ijm} + \phi_f EV_{ijf} \tag{11}$$

$$\delta_j(\theta_1) = \alpha_1 p_j + \mathbf{x}_j \bar{\beta} + \xi_j. \tag{12}$$

Further details about the estimation can be found in Appendix E.

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 (12) 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 of instruments 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. Decreasing winning odds push up demand (and hence prices) for houses in desirable locations, such as places close to the subways or the city center. The third set of IVs is the number of homes sold in the real-estate listing dataset in the two-month time window of a given home, which is also a proxy for market competition.

5 Estimation Results

We begin by presenting estimation results for the commuting mode choice model. Then we construct the ease-of-commuting index, which captures the value of commuting options for work trips based on home and work locations. Taking the ease-of-commuting index as an observed housing attribute, we then estimate the housing demand model.[29]

5.1 Commuting Mode Choice

We assume that the error terms in both the housing equation (2) and the commuting mode choice equation (3) have the type I extreme value distribution. 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 comes only from the interaction between the travel cost and income. 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) begins with interactions between year dummies (2010 or 2014) and mode-specific constants (car, taxi, bus, subway, walking, and biking). The implied VOT from these estimates is 0.757 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 0.342 of the hourly wage.

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

[29] 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. 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).

variables greatly improves the fit of the model and better captures the heterogeneity in mode choices across demographic groups. The VOT estimate is 33.9% of hourly wage. Columns (4) to (6) use a chi-square distribution with three degrees of freedom to approximate heterogeneous preference on travel time following Petrin (2002).[30] In addition to the random coefficient on travel time, Column (5) also allows a random coefficient on the mode of driving. Column (6) further incorporates random coefficients for each of the five travel modes (with walking as the reference group).

Our preferred specification is Column (6). The preference heterogeneity for different travel modes is assumed to be i.i.d. normal and 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 of scheduling constraints. Some commuters choose walking or biking for their exercise benefit. The dispersion on the preference parameters for all transit modes is quite large, suggesting significant heterogeneity for different modes. Adding these random coefficients leads to much stronger consumer sensitivity to travel cost. The average (median) VOT estimate is 95.6% (84.6%) of hourly wage and these estimates are within the range typically found in the recent literature.[31]

5.2 Housing Location Choice

We now turn to the estimation results of the housing demand model described in Section 4.2. We first construct the ease of commuting (EV_{ij}) for each member within household i based on parameter estimates from the travel choice model:

$$EV_{ijk} = \mathbb{E}_{\varepsilon_{ijk}}\left(\max_{m\in M_{ijk}} u_{ijkm}\right) = \log\left(\sum_{m\in M_{ijk}} \exp\left[\theta_m + \gamma_{1ik} time_{ijkm} + \gamma_2 cost_{ijkm}/y_i + w_{ijkm}\eta\right]\right), k \in \{Male, Female\}.$$

For each home in household i's choice set, we generate this measure separately for male (61% main borrower) and female (39% main borrower) members based on their work locations.[32] These two variables enter the housing demand as additional household-specific attributes. We first present the MLE estimates of household-specific preference parameters, and then discuss the IV estimates for coefficients in the mean utility.

[30] We winsorize the top and bottom 5% of the distribution to bound the distribution and to minimize the impact of outliers. The three degrees of freedom provide the best model fit.

[31] Appendix Figure A11 depicts the histogram of the VOT estimate in our sample. The empirical estimates of VOT in the literature 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). 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.

[32] If a family member is unemployed, we set $EV_{ij} = 0$ for that member, effectively ignoring this term in the decision process.

Table 4 reports the estimates of heterogeneous preference parameters for three specifications: without the EV terms, with the EV terms, and with random coefficients on the EV terms. The coefficient estimates from these three specifications are by and large similar, except for the coefficient on the interaction between age great than 45 and distance to key schools. Housing price is interacted with household income, which is used as an proxy for household wealth.[33] As expected, 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 homes 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 ¥18,000 (21,000) more on a home to save ¥1 in the male (female) member's work commute, or ¥185,000 (219,000) more to shorten the male (female) member's work commute by 10 minutes. The coefficient estimate on the EV term for the female member is 18% larger than that for the male member, suggesting that households prioritize the female member's ease-of-commute in housing choices. This is consistent with the descriptive evidence that females tend to live closer to their work locations (Appendix Figure A7). In addition, there is significant preference heterogeneity across households on the EV terms, e.g., due to unobserved household demographics.

We interact the age group dummies with the distance to the nearest signature elementary school. Enrollment to these top schools is restricted to the residents in the corresponding school district, and homes in these districts command a high premium. The baseline group is those with the primary borrower younger than age 30. The interaction coefficients in all specifications are negative and highly significant, though borrowers between age 30 and 45 exhibit the strongest preference for proximity to key schools, as they are most likely to have school age children.

We do not observe the household size. To capture preference heterogeneity on home size due to variation in household size, we use the age of the primary borrower as a proxy and interact age group dummies with home size. Older households have stronger preference for home 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.

Estimates for coefficients in the mean utility are reported in Table 5. Columns (1) and (2) use OLS, while columns (3)-(6) are from IV regressions. All regressions month-of-sample interacted with district fixed effects to capture time-varying changes in market conditions and amenities that could vary across the 18 districts in Beijing. Columns (2)-(6) also include neighborhood (158 different jiedaos) fixed effects to capture unobserved time-invariant neighborhood amenities. We use the three sets of IVs for housing prices that are discussed in Section 4.5: the average attributes of the homes within 3km outside the sample complex sold in a two-month time window of a given home; the interaction between the first set of IVs and the winning odds of the vehicle licence lottery; the number of homes sold in a two-month window. Our preferred specification

[33] The interaction itself only captures part of the consumer price sensitivity since housing price also enters the mean utilities (household-invariant utilities).

is Column (6) with all instruments. The first stage F- statistics is 14.22, and the over-identification test cannot be rejected at 10% level.

Across all columns, the price coefficient estimate is negative and statistically significant. The IV estimates are larger (in magnitude) than the OLS estimates, consistent with the findings in the demand literature that unobserved product attributes bias OLS estimate toward zero. The average price elasticities vary from -1.34 to -1.94 in Columns (4)-(6), suggesting elastic housing demand.[34] The coefficient estimates from IV regressions in columns (3) to (6) are all intuitively signed. Households prefer larger homes and homes closer to the signature schools, but dislike older buildings and homes that are far away from parks.

Based on parameter estimates from the last columns in 4 and 5, the sample average of the implied income elasticity of housing demand and the income elasticity of marginal driving cost is 0.10 and 0.78, respectively. To our knowledge, these are the first estimates of the two elasticities based on data from China. Our estimate of the income elasticity of demand for housing size is somewhat smaller than those based on the US data 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 the (condo) interior size rather than the lot size.

6 Counterfactual Simulations

We now utilize the estimates from the housing and travel mode choices to conduct counterfactual simulations. We examine five policy scenarios: the 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 last two counterfactual analyses examine combinations of different policy mix. 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 a distance-based congestion charge to achieve the same level of congestion reduction as the 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 simulation 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 F.

Before we present simulation results, we first validate the structural model by comparing the model's

[34]To evaluate the impact of ignoring the work commuting attribute (the EV terms) on price elasticities, Appendix Table A4 reports the second-stage regression results 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 demand estimation.

predictions to the mortgage data. We simulate the market equilibrium under the 2008 subway network with and without the driving restriction. Then we examine the effect of the driving restriction on the housing price gradient with respect to the subway access using the model's predicted equilibrium housing price. The results are reported in Appendix Table A5. 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 driving restriction policy dummy is -0.01 compared with -0.023 (with a standard error of 0.013) in the regression with observed data.

6.1 Travel and Housing Choices and Equilibrium Prices

We begin by considering the simulation results with sorting in Table 6. To incorporate sorting, we allow households to re-optimize their housing locations and solve for the new market equilibrium under each scenario. 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 reports changes in the share of mode choices and equilibrium traffic speed under each scenario, Panel B displays 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 the median (poor) to reflect distributional considerations following Section 2.

Several features of endogenous congestion and household sorting have important implications on the policy effectiveness in terms of congestion relief. Sorting introduces two countervailing forces under a driving restriction. On one hand, a driving restriction incentivizes households to live closer to work. This reduction in the driving distance further magnifies the alleviation of congestion as a result of travel mode changes when households substitute away from driving. On the other hand, congestion reduction from the driving restriction improves the driving speed, makes driving less costly, and hence disproportionally increases driving among those with a long commute. As the equilibrium congestion is affected by both intensive and extensive margins, the increase in the extensive margin dampens the effectiveness of a driving restriction policy.

In contrast, as a distance-based policy, congestion pricing affects driving in the same direction for both the intensive and extensive margins and delivers a larger congestion reduction with sorting.[35] Congestion pricing induces mode shifting in the same directions as a driving restriction, but there are two key differences. First, while congestion pricing generates a modest driving reduction among high-income households, it leads to a much bigger reduction among low-income households. The large response from the low-income group is driven by the fact that low-income households are more sensitive to the travel cost and hence to congestion charges. Second, although the level of congestion reduction is the same under the two policies, the share of commuting trips via driving remains higher under congestion pricing. This is because distance-based congestion pricing reduces congestion through an intensive margin by disproportionally reducing longer driving

[35] We set the congestion price to be ¥0.92/km to achieve the same congestion reduction as that under a driving restriction.

trips.

Despite the large increase in subway usage, subway expansion leads to the smallest congestion reduction. Column (4) presents the impact of subway expansion from the 2008 network to the 2014 network. Traffic speed increases by about 7 percent with sorting, only about 40% of what is achieved under the driving restriction and congestion pricing, 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).[36] Our analysis shows that the effectiveness of subway expansion is attenuated by sorting as illustrated in Figure 6. Both income groups move farther away from work and commute longer distances with a more extensive subway network. This additional 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). The results on the further separation of workplace and residence from subway expansion corroborate with the evidence in Gonzalez-Navarro and Turner (2018) and Heblich et al. (2020).

Nonetheless, the expansion dramatically increased subway access for both income groups: the distance to the nearest subway station from home is reduced by about 80% for both groups. As a result, the expansion increases subway ridership by 51% and 56% among high- and low-income groups, respectively. Subway expansions reduce the share of all other travel modes, though the reduction in taxi and bus trips is more pronounced. Low-income groups are much more likely to substitute from other travel modes toward subway, due to their larger price sensitivity. Overall, the reduction in the driving share of commuting trips as a result of the subway expansions is about 43% of that observed under driving restriction and congestion price, leading to smaller congestion relief. While the substitution away from bus, bike, and walk trips toward subway trips does not alleviate traffic congestion, it improves welfare by offering quicker and hence better commuting choices for some trips.

We calibrate the congestion charge so that both congestion pricing and driving restrictions achieve the same level of congestion reduction under the 2008 subway network. At the same level of congestion charges, congestion pricing is more effective than driving restrictions under the 2014 subway network. That is, the market-based demand policy and the supply side policy exhibit complementarity by producing a stronger aggregate impact.[37] The results reflect two underlying countervailing forces. On the one hand, subway expansion increases the attractiveness of using subways 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

[36] 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.

[37] 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.

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.

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 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 policy in that the larger subway network makes substitution away from driving easier under driving restriction or congestion pricing. Indeed, as the subway becomes a 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.

It is instructive to compare these results to those without sorting that are presented in Appendix Table A6.[38] The comparison illustrates that sorting reinforces the impact of congestion pricing on congestion reduction but weakens the impact of subway expansion. Finally, the optimal congestion price (with revenue recycling) that maximizes consumer surplus is ¥1.2/km (the speed increase is 3.81km/h) without sorting compared to ¥1.4/km (the speed increase is 4.70km/h) with sorting under the 2014 subway network (as shown in Panel (b) of Figure 8 below).

Spatial Distribution of Changes While driving restrictions and congestion pricing both reduce congestion, the impacts on the spatial distribution of households differ under sorting. Consistent with the reduced-form evidence, a driving restriction induces high-income households to move closer to subway, while pushing low-income households to move farther away from work and subway. In contrast, congestion pricing induces both high- and low-income groups to move closer to work, hence reducing "wasteful commuting" for both groups. As congestion pricing is distance-based, it induces a stronger sorting than driving restriction. As illustrated in Figure 6, driving restrictions lead to small changes in commuting distance and often in opposite directions across neighborhoods, but congestion pricing leads to a larger reduction in commuting distance in nearly all neighborhoods relative to the no-policy scenario. In terms of subway access, both driving restrictions and congestion pricing make high-income households move closer to the subway while low-income households move further away from the subway compared to the baseline scenario. The exact opposite effect on distance between home and subway for the two income groups is driven by the fact that the subway network is the same for all households and therefore households have to compete for the closeness to subways in a zero-sum game, but work locations differ across households so a Pareto improvement in commuting distance is possible.

In Figure 7, while both driving restriction and congestion pricing increase the prices of homes that are closer to work centers, the impact is stronger under congestion pricing driven by the distance-based nature of

[38]The congestion price is kept at ¥0.92/km as in Table 6 with sorting to facilitate comparison.

congestion pricing. Under congestion pricing, housing prices in northwest parts of the city (near work centers) would increase by about 2,000 ¥/m^2 while those in some parts of southeast that are far from work centers and public transit would decrease by 2000 ¥/m^2 (from a baseline average price at 24022 ¥/m^2). Subway expansion has opposite spatial impacts on housing price: the price increase is mainly observed among homes farther away from the city center (where the public transportation is poor prior to the expansion) but also along the new subway lines as shown by the green lines in Panel (c). Home prices increase by as much as 4000 ¥/m^2 in some southwest parts of the city, where the subway expansion is greatest and the prices have been the lowest historically. With both the subway expansion and congestion pricing, the price impacts of subway expansion dominate those from congestion pricing.

To understand the differential impact on home prices with respect to access to subway, Appendix Figure A12 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 homes whereby the subway expansion reaches to cheaper homes farther away from the city center.[39]

With Sorting and Supply Adjustment Finally, we present the results with sorting in Table 7 and additionally allowing the housing supply to adjust. Housing supply is modeled as a constant elasticity function of local home prices.[40] To fix ideas of how incorporating the supply-side changes our previous findings, think about a home whose price increases after a policy. Now housing supply of that home will increase. Hence in the new equilibrium, we expect part of housing price changes to be absorbed by the increasing housing supply. The additional increases in the housing supply of attractive homes will allow more efficient sorting, hence magnifying the sorting effects compared to the case when the housing supply is fixed.

This intuition is supported by our simulation results. In terms of the driving speed, housing supply adjustments make the congestion pricing policy more effective (the driving speed improvement increases from 3.13km/h to 3.26 km/h), while attenuating the gains from subway constructions (from 1.49km/h to 1.13 km/h). These changes could be driven by both the intensive and the extensive margin. With a varying housing supply, distance to work under congestion pricing further decreases relative to the case where the supply is fixed (from -0.15km to -0.26 km for high-income male member and from -0.07 km to -0.19 km for low-income male member), while the distance to work under subway constructions increases relative to the case where the

[39] Similarly, from Figure A13, 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 homes close to the subway more attractive for everyone, congestion pricing, being a distance-based policy, makes homes 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 homes close to the subway.

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

supply is fixed (from +0.33 km to +0.76 km for high-income male member and from +0.15 km to +0.61 km for low-income male member). Driving probability, on the other hand, does not change significantly when supply adjustment is allowed. Hence we conclude that the changes in speed should mostly be contributed to intensive margin. In other words, the supply-side adjustment under congestion pricing increases the supply of homes in the city center and allows people to live even closer to their work, which shortens their commuting trips and magnifies the anti-sprawling effects. The supply-side adjustment under subway construction increases the supply of homes in suburban areas, making people live farther away from their work and exacerbating the sprawling effects. We elaborate on the welfare consequences of the supply adjustment in the next section.

6.2 Welfare Analysis

Panel C in Table 6 and 7 as well as Appendix Tables A6 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 budget. Subway construction and operation are funded by a head tax while the revenue from congestion pricing is recycled back to households via a lump sum. The discussion in this section focuses on our benchmark results that are presented in Table 6.

Since transportation infrastructure such as subways are durable, we assume a 30-year time-span during which the capital cost should be recouped. The choice of the time span matters for the magnitude of the welfare but does not qualitatively affect the comparison across the policy scenarios. To be conservative, we assume that households only benefit from commuting trips and ignore utilities they derive from non-commuting trips.[41] A related issue is the utility function specification where the total housing price rather than rental price is used. So the numbers on consumer surplus reported below should be considered as a discounted lifetime utility over a period of 30 years.[42]

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 Table 6 and Table A6.[43] There are two opposing effects 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 losses in consumer surplus as it removes the choice of driving from households' choice set one day a week (equivalent to shifting the driving demand curve downward). The second effect dominates: driving restrictions are associated with a ¥92 thousand loss per household. The welfare loss is larger for high-income households because they are more likely to have cars and commute via driving (a ¥165 thousand loss per high-income household and a ¥18 thousand loss per low-income household). Sorting exacerbates the welfare loss by 1% and 2% for high- and low-income groups, respectively.

[41] Work trips account for about 60% of all trips and 75% of the total travel distance in the 2014 travel survey.

[42] 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.

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

In contrast to the driving restriction policy, congestion pricing disproportionally affects 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 recycling of the congestion revenue that is uniform across income groups, congestion pricing leads to a welfare gain overall. This highlights the role that revenue from congestion pricing can play in addressing equity concerns. Sorting strengthens congestion reduction (an additional 0.13 km/h increase with sorting, a 4% increase) and enhances welfare gain from congestion pricing (an additional ¥5.8 thousand per household from sorting, a 10% increase), consistent with the finding in Langer and Winston (2008) based on a cross-section analysis for 98 US cities.

Figure 8 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 the 2008 and 2014 subway networks, respectively. At the optimal levels of congestion pricing, sorting would increase consumer welfare by 20%-30%, 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 the 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 (26.2 km/h with sorting versus 25.3 km/h without sorting). The figure also shows that under a wide range of levels of congestion pricing (<¥2.5/km) and different sorting assumptions, consumer welfares are always positive. This indicates that congestion pricing is likely to be an effective tool even when governments cannot gauge the exact optimal pricing level a priori.

In our simulation table, we assume away the implementation cost of the congestion pricing system in Beijing because the congestion pricing has yet to be implemented. Singaporean government's implementation of a satellite based road pricing system in 2021 provides a back of envelope calculation on the cost of a congestion toll system.[44] The system costs Singaporean government around $ 400 million, which is roughly what would cost Beijing to adopt a similar system. This cost translates into around 1,000 RMB per household in Beijing, likely to be negligible in our welfare analysis (under optimal pricing, one-year operation of congestion pricing will create 3,000 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 reduces 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

[44]For more information on Singapore's road pricing syste, refer to https://www.zdnet.com/article/singapore-readies-satellite-road-toll-system-for-2021-rollout/

high-income households exceeds their tax burden in both with-sorting and without-sorting scenarios, 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) of Table 6 also show that the revenue from congestion pricing (107.8 thousand ¥per household) could fully cover the costs of subway expansions (103.0 thousand ¥per household). 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 work 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 homes based on the job locations of each working members. This home-work 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 network, respectively. Allowing for equilibrium sorting could have significant implications on welfare estimates of urban transportation policies: sorting accounts for over 20-

30% 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 work, which could disadvantage low-income households in the long run. Congestion pricing incentivizes residents to live closer to their work 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 ¥0.92/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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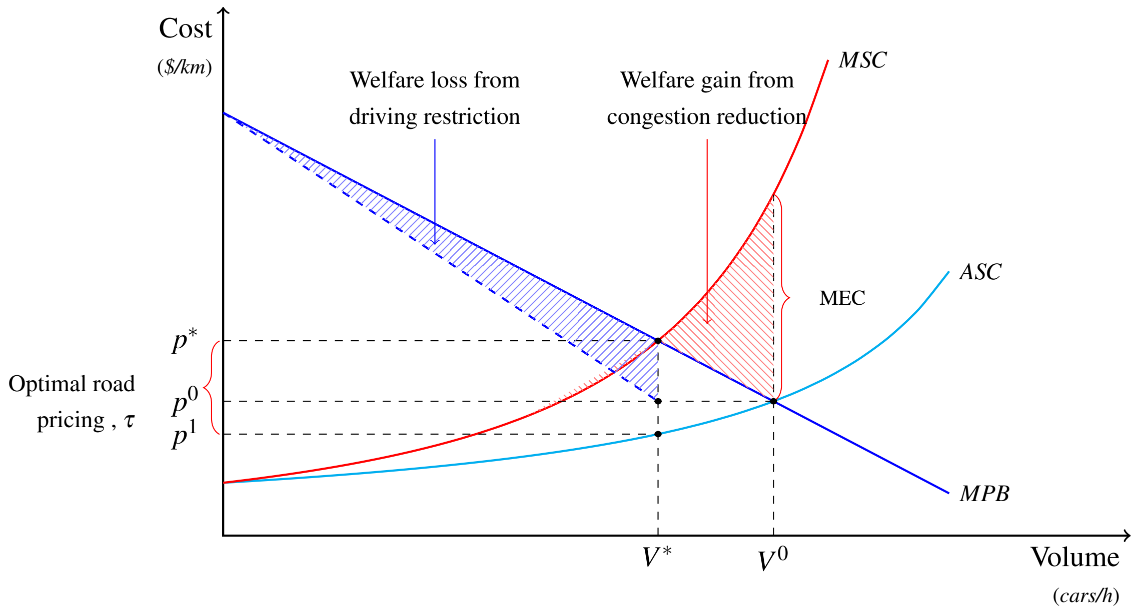
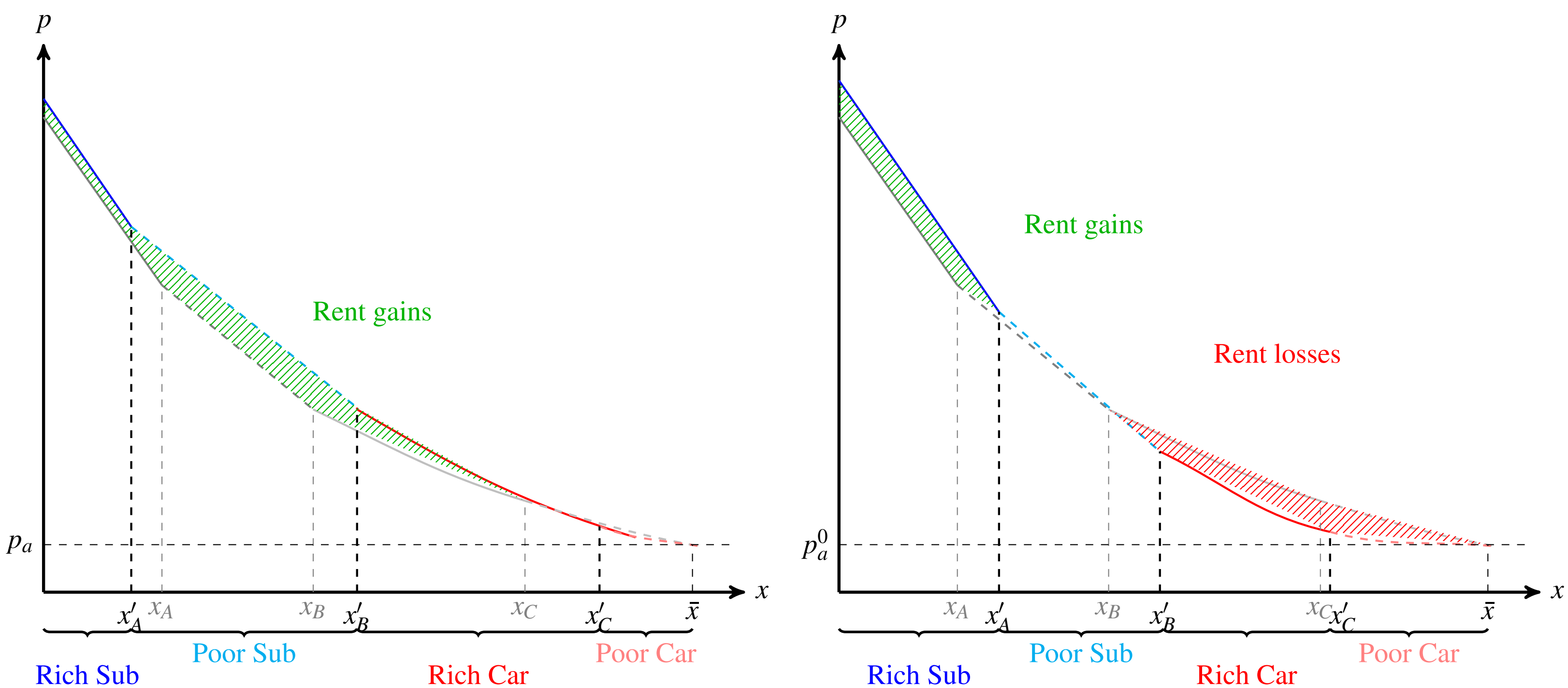
Figure 1: Traffic under Congestion Pricing and Driving Restriction



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

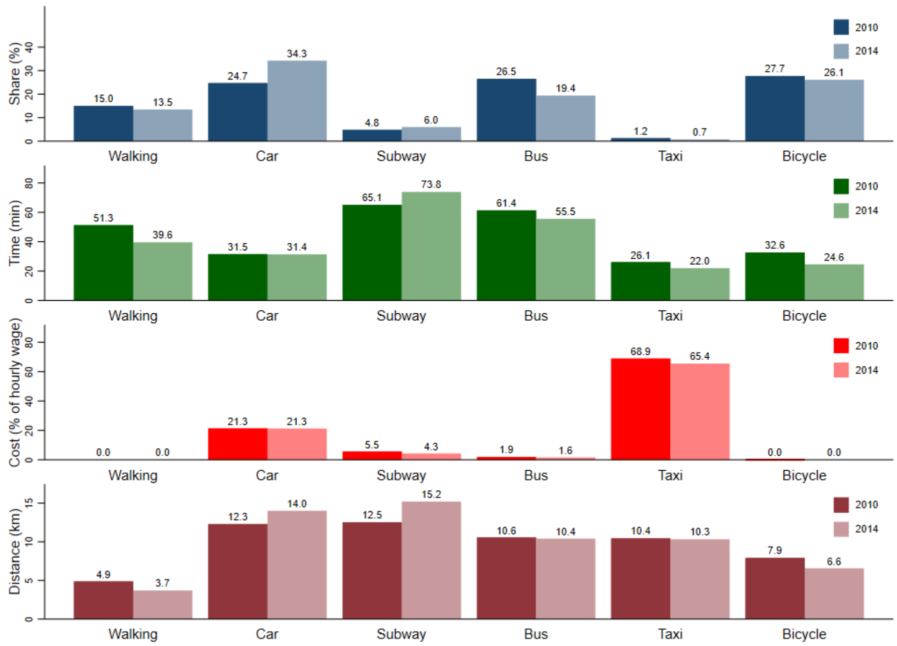
(a) Congestion Pricing (b) Driving Restriction



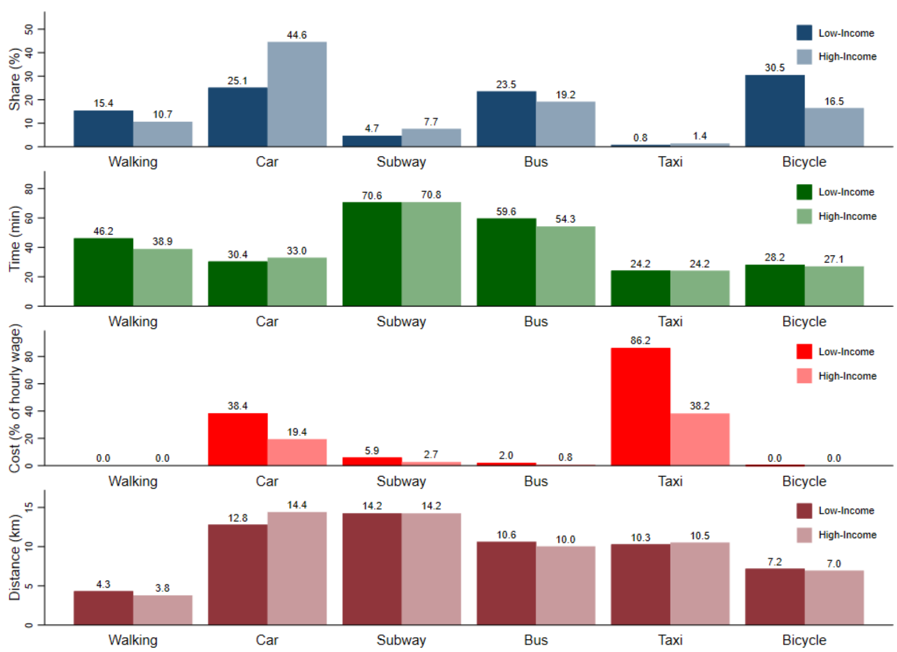
Note: This figure illustrates the capitalization of commuting cost changes into the housing market with sorting. A full exposition of the individual bid-rent curves in the diagram is provided in the Appendix as well as the underlying assumptions and equilibrium conditions. The left panel shows the effect 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



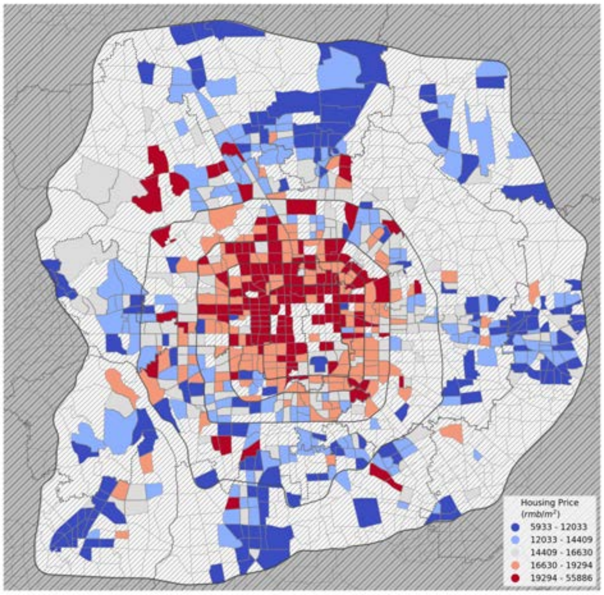
(b) High income vs. Low Income



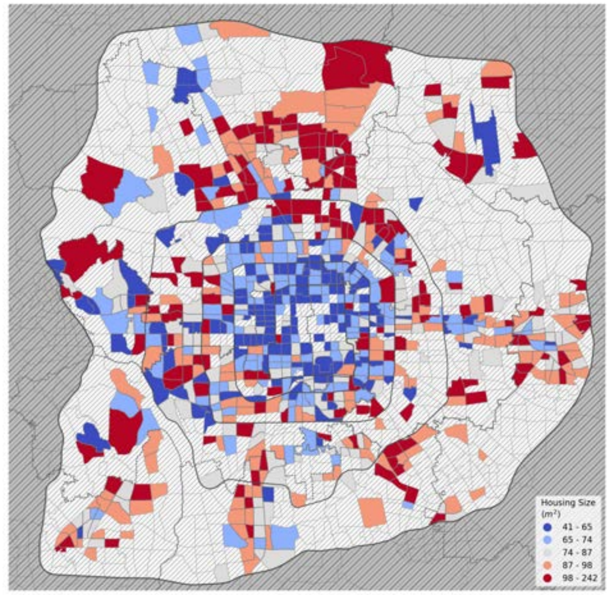
Note: This figure plots trip share, time, and costs by different modes for work commuting trips in the Beijing Household Travel Survey of 2010 and 2014. There are six main trip modes: walk, bike, bus, subway, car, and taxi. For bus and subway trips, they could include segments with other modes but we characterize them as the bus and subway trips. Trips using both bus and subway are rare (less than 3% in the data and we drop them in the analysis.) The mode shares are based on chosen modes in the data. Travel time, cost (defined as % of hourly wage), and distance are constructed as shown in Appendix **??**. The numbers in the figures are for the 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

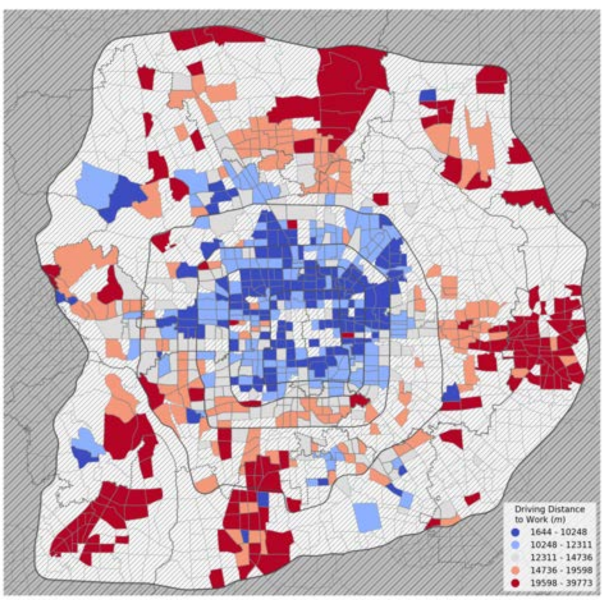
(a) Housing Price (¥/m^2)



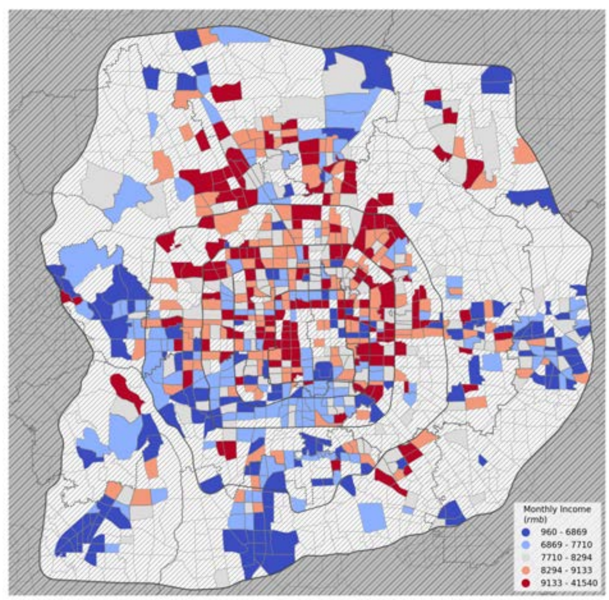
(b) Housing Size (m^2)



(c) Distance to Work (m)

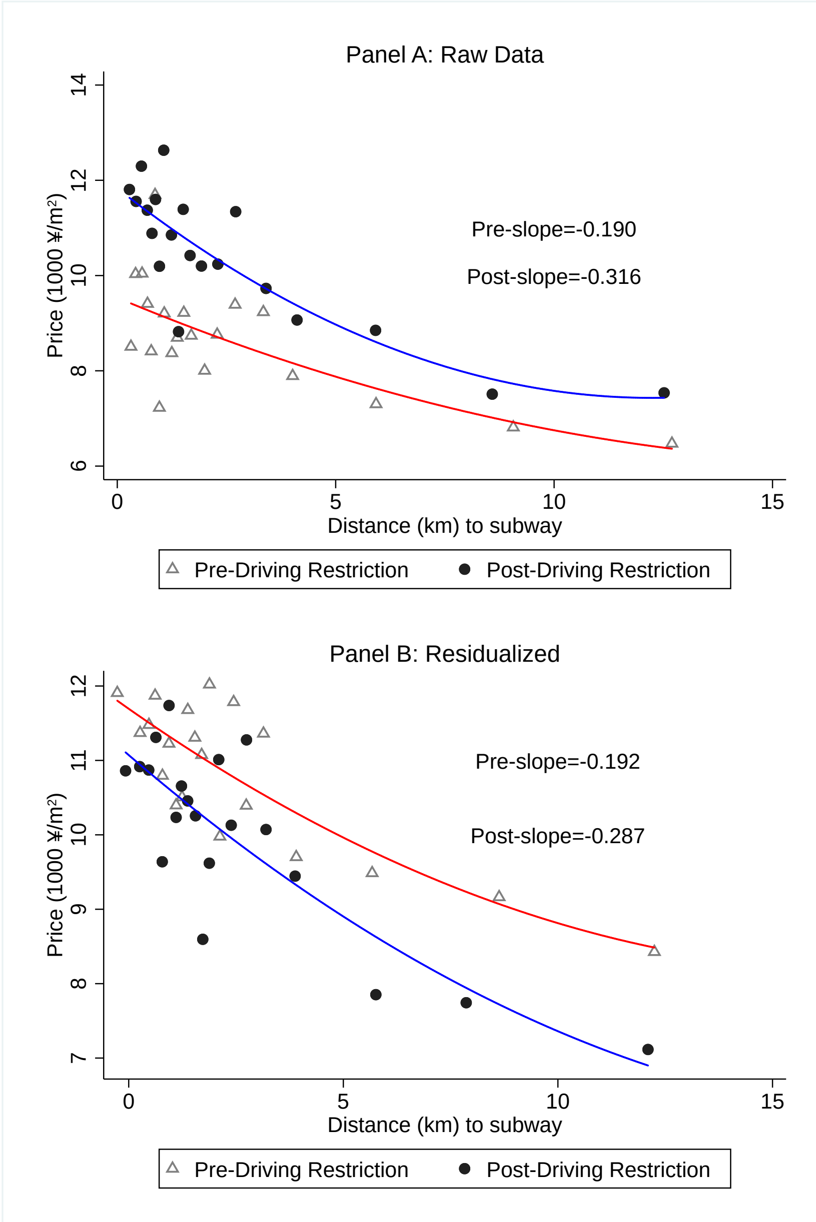


(d) Monthly Household Income (¥)



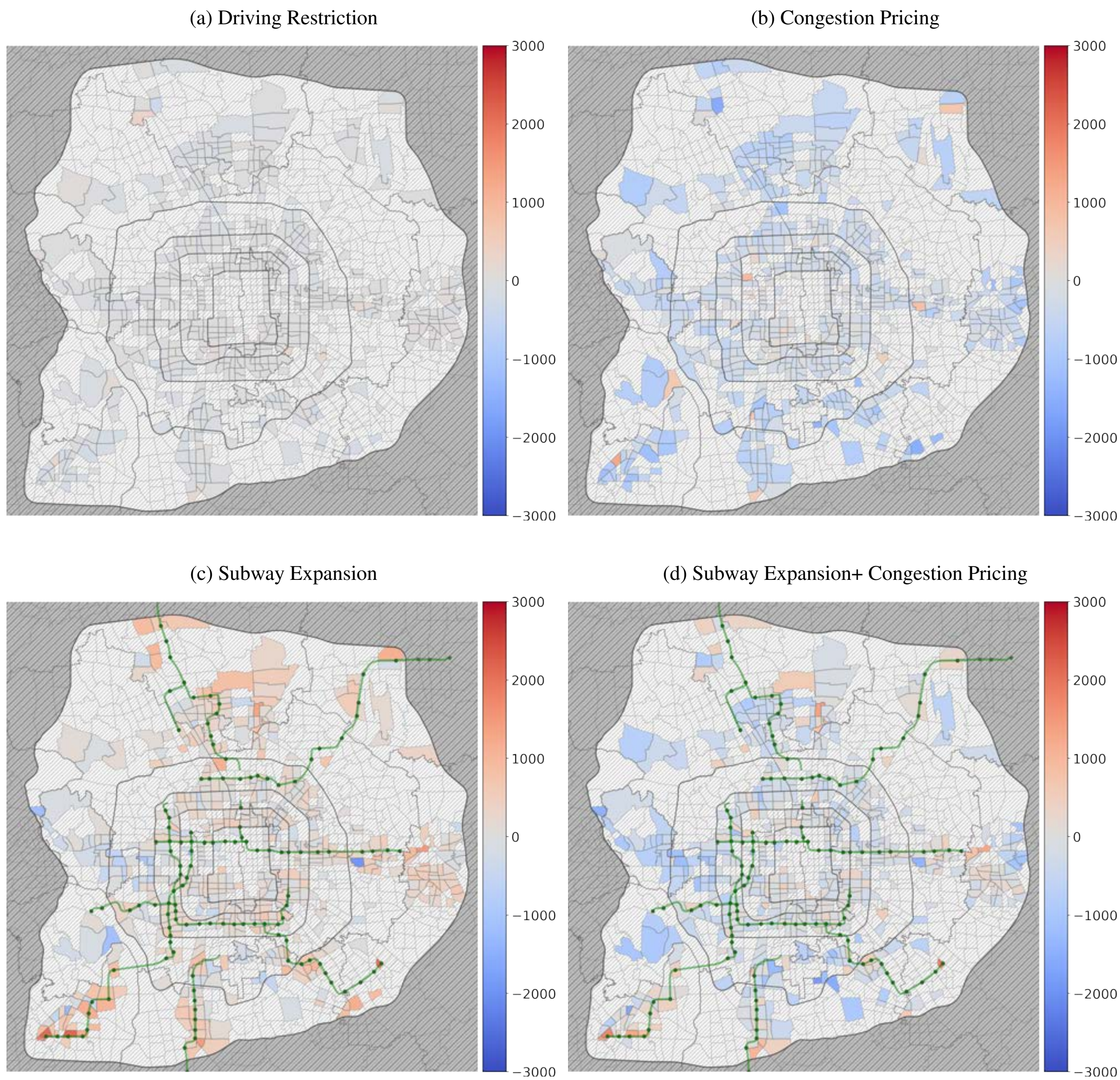
Note: This figure plots the averages of key housing and household attributes by Traffic Analysis Zone (TAZ) based on mortgage data from 2006 to 2014. The values are the averages across homes in the TAZ from the mortgage data during the data period. Distance to work is the driving distance to work for 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



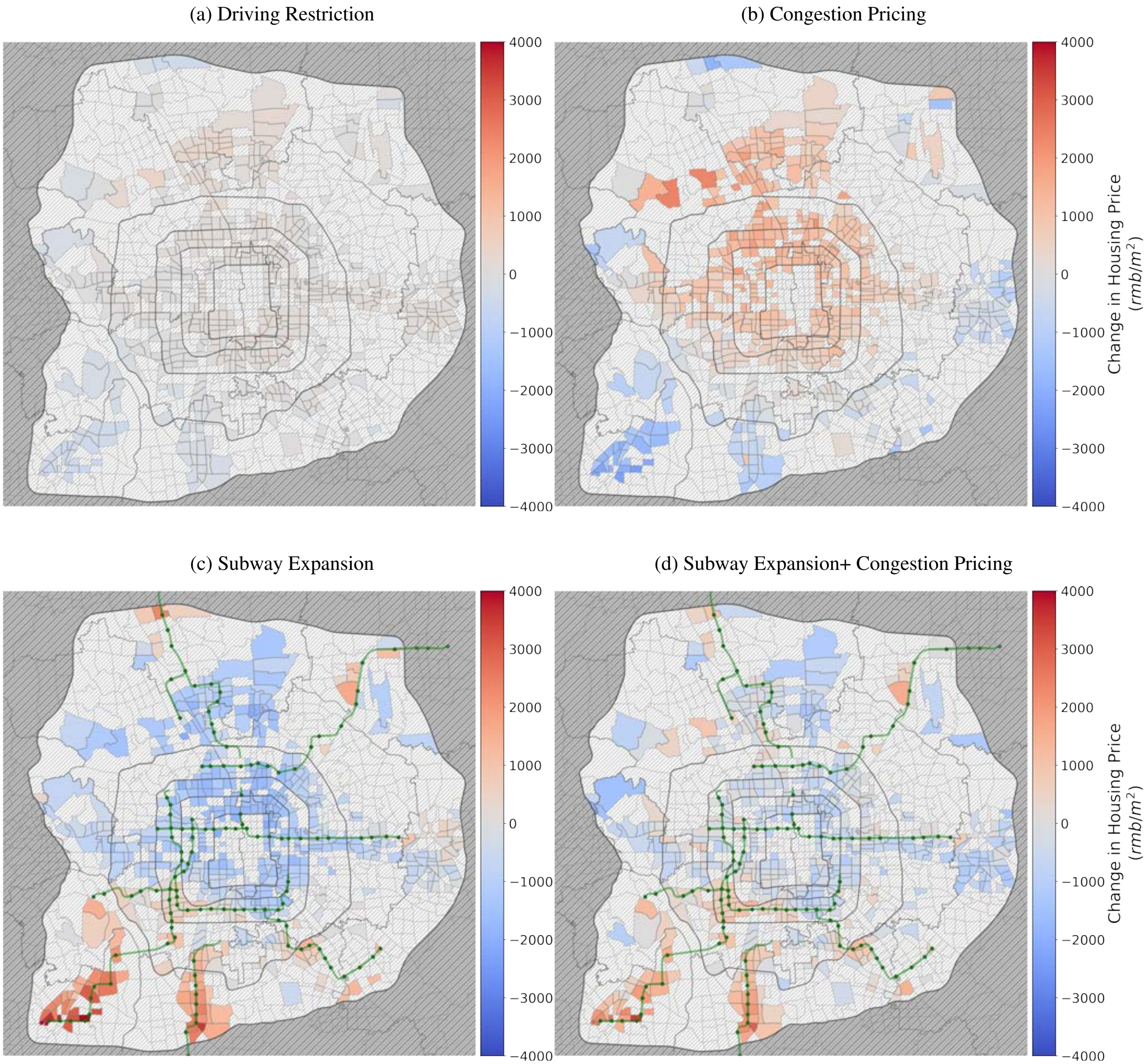
Notes: These binned scatterplots show housing price per square meter against distance to subway before and after the driving restriction goes into effect in Beijing. The sample spans 24 months before and after the policy starting point (July 2008). The top panel is the binned scatter plot based on the 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: Changes in Commuting Distance from Simulated Policies (in meters)



Note: This figure illustrates simulated changes in commuting distance under different counterfactual policy scenarios (relative to the baseline scenario of no policy). The results are based on the simulations in Table 6. 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.

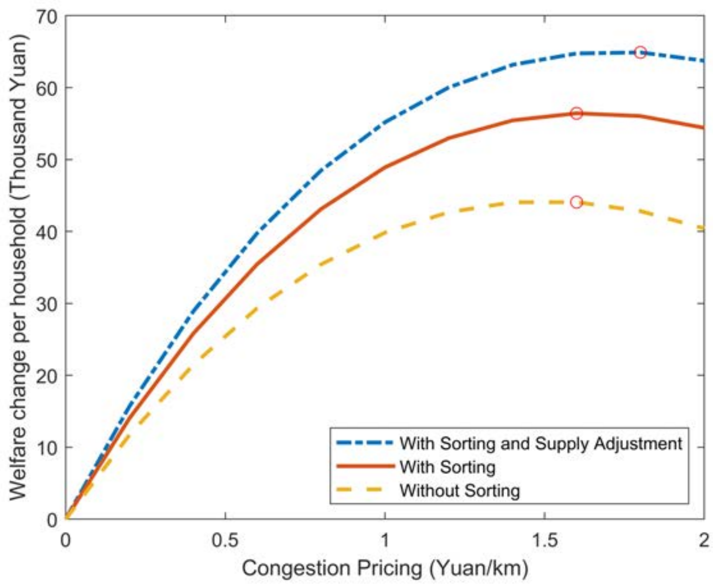
Figure 7: Changes in Housing Prices from Simulated Policies (¥$/m^2$)



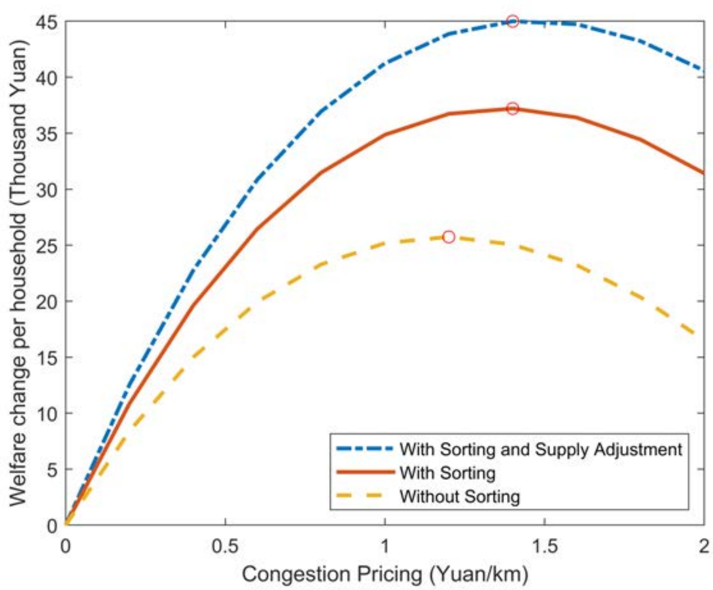
Note: This figure illustrates simulated changes in home prices under different counterfactual policy scenarios (relative to the baseline scenario of no policy). The results are based on the simulations shown in Table 6. Each cell represents a TAZ. Warmer colors corresponds to an increase in price while 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 8: Optimal Congestion Pricing under 2008/2014 Subway Network

(a) 2008 Subway Network



(b) 2014 Subway Network



Note: The plot shows the welfare change with respect to congestion pricing under 2008/2014 subway network, 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 ¥1.4/km for 2008 subway system and ¥1.2/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

Note: The table reports respondent and trip characteristics of all work commuting trips within the 6th ring road from 2010 and 2014 Beijing Household Travel Survey.Travel time and travel cost variables are those associated with the chosen modes, and are constructed as shown in Appendix **??**. Distance<2km and Distance within 2-5km denotes straight-line distance and captures short to medium-distance commuting trips. The travel mode shares are shown in Figure 3.

Table 2: Summary Statistics of Housing Data

	Mean	SD	Min	Max
Housing 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)	-1.194	-0.270	-0.191			
	(0.082)	(0.006)	(0.006)			
Travel Cost/Hourly Wage (γ_2)	-1.578	-0.788	-0.565	-1.411	-1.424	-2.531
	(0.324)	(0.028)	(0.034)	(0.041)	(0.052)	(0.065)
Random coefficients on travel time (μ_γ)						
Travel Time				-0.955	-0.885	-0.931
				(0.008)	(0.008)	(0.012)
Random coefficients on mode-specific constants (σ_m)						
Driving					3.394	3.391
					(0.049)	(0.054)
Subway						4.470
						(0.142)
Bus						3.851
						(0.056)
Bike						3.887
						(0.054)
Taxi						4.203
						(0.353)
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	-116287	-109929	-91119	-87353	-85099	-77706
Implied mean VOT	0.757	0.342	0.339	1.760	1.615	0.956
Implied median VOT	0.757	0.342	0.339	1.557	1.429	0.846

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 (winsorized 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_m of those normal distributions for each travel mode 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 Para	No EV SE	With EV Para	With EV SE	EV and Random Coef. Para	EV and Random Coef. SE
Demographic Interactions						
Price (in 1 million RMB)*ln(income)	0.965	0.007	1.005	0.008	1.030	0.016
Age in 30-45*ln(distance to key school)	-0.329	0.004	-0.391	0.005	-0.420	0.010
Age $>$ 45*ln(distance to key school)	-0.074	0.009	-0.111	0.010	-0.123	0.021
Age in 30-45*ln(home size)	1.343	0.014	1.443	0.015	1.486	0.029
Age $>$ 45*ln(home size)	2.394	0.028	2.665	0.031	2.746	0.061
EV_{Male}			0.709	0.026	0.755	0.006
EV_{Female}			0.833	0.026	0.893	0.006
Random Coefficients						
$\sigma(\text{EV}_{Male})$					0.379	0.013
$\sigma(\text{EV}_{Female})$					0.482	0.012
Log-likelihood	-206829		-170057		-168808	

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 (ease of commuting); the second specification does; the third specification further controls random coefficients on EV terms. EV is constructed 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 (1)	OLS (2)	IV1 (3)	IV1+IV2 (4)	IV3 (5)	All (6)
Price (million RMB)	-2.240***	-2.191***	-6.283***	-6.454***	-7.091***	-6.596***
	(0.186)	(0.184)	(0.867)	(0.583)	(1.640)	(0.534)
Ln(home size)	-3.648***	-3.797***	3.331**	3.631***	4.721	3.879***
	(0.257)	(0.261)	(1.505)	(1.022)	(2.927)	(0.969)
Building age	-0.043***	-0.029***	-0.125***	-0.129***	-0.144***	-0.132***
	(0.007)	(0.006)	(0.020)	(0.014)	(0.040)	(0.013)
Floor to Area Ratio	-0.006	-0.009	-0.023	-0.023	-0.019	-0.023
	(0.034)	(0.025)	(0.032)	(0.033)	(0.036)	(0.034)
Ln(dist. to park)	0.210***	0.074	-0.389***	-0.408***	-0.475**	-0.424***
	(0.069)	(0.057)	(0.117)	(0.101)	(0.222)	(0.103)
Ln(dist. to key school)	0.950***	0.782***	0.323**	0.304**	0.210	0.288**
	(0.080)	(0.137)	(0.139)	(0.121)	(0.213)	(0.118)
Year-Month-District FE	Y	Y	Y	Y	Y	Y
Neighborhood FE		Y	Y	Y	Y	Y
First-stage F			10.5	14.2	9.9	14.2
Avg. Price elasticity	2.96	2.96	-1.04	-1.34	-1.94	-1.44

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. The floor-area ratio of the complex, a measure of complex density, is 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 homes (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 home. 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 homes 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: 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)	
Household Income Relative to Median	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Panel A: Travel outcomes												
Drive	41.65	21.44	-6.07	-2.59	-2.90	-4.54	-2.14	-1.66	-7.44	-3.84	-4.59	-5.60
Subway	9.02	10.77	1.09	0.66	0.75	0.89	4.62	6.06	5.59	6.42	5.12	6.70
Bus	22.44	30.47	1.51	0.26	0.42	0.96	-1.54	-2.53	-0.06	-1.95	-0.92	-1.28
Bike	15.96	24.01	1.54	0.63	0.63	1.48	-0.80	-1.64	0.52	-1.08	-0.27	-0.38
Taxi	2.20	1.32	0.70	0.34	0.51	0.46	-0.16	-0.11	0.42	0.17	0.29	0.27
Walk	8.74	11.99	1.23	0.70	0.59	0.74	0.02	-0.13	0.98	0.28	0.37	0.29
Speed	21.49		3.13		3.13		1.49		4.44		4.61	
Panel B: Housing market outcomes												
Male member's distance to work (km)	19.45	18.88	0.01	0.02	-0.15	-0.07	0.33	0.15	0.37	0.15	0.15	0.08
Female member's distance to work (km)	17.54	11.95	0.01	0.01	-0.12	-0.05	0.39	0.21	0.43	0.21	0.24	0.17
Distance to subway (km)	5.33	4.30	-0.03	0.03	-0.02	0.02	-4.14	-3.44	-4.14	-3.44	-4.14	-3.44
Panel C: Welfare analysis per household (thousand ¥)												
Consumer surplus (+)			-165.3	-19.6	-76.8	-61.3	220.3	100.0	47.8	77.6	131.9	40.2
Toll revenue (+)					115.9	115.9					107.8	107.8
Subway cost (–)							103.0	103.0	103.0	103.0	103.0	103.0
Net welfare			-165.3	-19.6	39.1	54.5	117.3	-3.0	-55.2	-25.4	136.7	44.9

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 homes. The detailed simulation procedure can be found in F. This table shows results with sorting and supply adjustment. In particular, 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) shows the differences from column (1). Driving restriction prohibits driving in one of five work days. Congestion pricing is ¥0.92 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 100% of 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 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)	
Household Income Relative to Median	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Panel A: Travel outcomes												
Drive	41.65	21.44	-6.08	-2.60	-2.90	-4.52	-2.32	-1.80	-7.55	-3.93	-4.71	-5.72
Subway	9.02	10.77	1.10	0.68	0.78	0.94	5.00	6.57	5.98	6.95	5.42	7.13
Bus	22.44	30.47	1.52	0.27	0.38	0.87	-1.52	-2.48	-0.06	-1.91	-0.92	-1.25
Bike	15.96	24.01	1.54	0.62	0.62	1.45	-0.86	-1.78	0.42	-1.26	-0.33	-0.51
Taxi	2.20	1.32	0.70	0.34	0.51	0.47	-0.20	-0.15	0.38	0.13	0.27	0.24
Walk	8.74	11.99	1.23	0.69	0.62	0.80	-0.10	-0.36	0.83	0.02	0.28	0.10
Speed	21.49		3.13		3.26		1.13		4.04		4.39	
Panel B: Housing market outcomes												
Male member's distance to work (km)	19.45	18.88	0.02	0.03	-0.26	-0.19	0.76	0.61	0.84	0.63	0.47	0.44
Female member's distance to work (km)	17.54	11.95	0.02	0.02	-0.21	-0.14	0.76	0.60	0.82	0.62	0.52	0.48
Distance to subway (km)	5.33	4.30	-0.04	0.01	-0.09	-0.06	-4.13	-3.45	-4.14	-3.44	-4.14	-3.45
Panel C: Welfare analysis per household (thousand ¥)												
Consumer surplus (+)			-165.4	-18.7	-65.7	-59.1	187.4	105.3	18.3	84.8	108.4	45.9
Toll revenue (+)					115.2	115.2					108.9	108.9
Subway cost (–)							103.0	103.0	103.0	103.0	103.0	103.0
Net welfare			-165.4	-18.7	49.5	56.0	84.4	2.3	-84.7	-18.2	114.3	51.9

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 workdays. Congestion pricing is ¥0.92 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 100% of 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.