Road Rationing Policies and Housing Markets

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Abstract

Canonical urban models postulate transportation cost as a key element in determining urban spatial structure. This paper examines how road rationing policies impact the spatial distribution of households using rich micro data on housing transactions and resident demographics in Beijing. We find that Beijing's road rationing policy significantly increased the demand for housing near subway stations as well as CBD. The premium for proximity is stable in the periods prior to the driving restriction, but shifts significantly in the aftermath of the policy. The composition of households living close to subway stations and Beijing's CBD shifts toward wealthier households, consistent with theoretical predictions of the monocentric city model with income-stratified transit modes. Our findings suggest that city-wide road rationing policies can have the unintended consequence of limiting access to public transit for lower income individuals.

Keywords: road rationing, housing markets, urban structure

JEL Classification Codes: R21, R41

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1 Introduction

At least 75 million people around the world live in cities with license-plate based driving restrictions. In an effort to combat air pollution and congestion, these road rationing policies restrict drivers from entering urban centers on particular days of the week during peak commute times.[1] Since Athens, Greece implemented the first of these alternate-day travel restrictions in 1982, permanent adoption of road rationing policies have increased steadily over the past three decades among some of the world's largest cities. For instance, Mexico City adopted the Hoy No Circula ("One Day Without a Car") program in 1989, restricting drivers from entering the city center one day per week. Bogata adopted the Pico y Placa ("Peak and License Plate") program in 1998, banning vehicles from driving during peak hours twice per week based on their license plate number. Sao Paulo, Brazil; Santiago, Chile; and Quito, Ecuador have similar permanent driving restrictions. Since the early 2000's, adoption of these policies has accelerated outside of South America into Asian and European cities (see Figure 1).

How have these driving restrictions impacted decisions on where to live? Despite growing adoption of road rationing policies and interest among scholars in their environmental effects (Davis 2008; Viard and Fu 2015; Carrillo et al. 2016; Zhang et al. 2017; Barahona et al. 2018), we know very little about the impacts of these policies on housing markets or their distributional implications. Cities are a physical manifestation of people's desire to eliminate transportation costs. Thus, driving bans will likely affect not only pollution and congestion, but the ways in which people sort in space. In this paper, we provide the first empirical evidence of how a city-wide driving restriction affects the spatial distribution of wealth. We show that urban road rationing policies can have potentially regressive consequences on access to economically important parts of cities through the housing market.

Our approach relies on the monocentric model of urban land use to determine how a road rationing policy affects income and housing prices across urban space. Developed by Alonso (Alonso 1964), Muth (Muth 1967), and Mills (Mills 1967) (hereinafter, "AMM"), the monocentric city model argues that land prices, population, and employment densities diminish with distance from an exogenous urban core. The model argues that housing prices per unit will increase near the city center as shocks like a road rationing policy increase the cost of transportation. The AMM model also provides a framework to characterize the spatial distribution of wealth within a city. However, the model's prediction on income sorting is indeterminant: lower *or* higher income households could occupy housing

[1] Air pollution is a primary concern for many urban areas. Over 80% of the world's major cities fail to meet World Health Organization guidelines on air quality (World Health Organization 2019). Emissions from vehicles is a particular concern in several developing nations, contributing to nearly 50% percent of particulate matter in Beijing (Viard and Fu 2015) and nearly 20% in Delhi (Jain 2018).

closest to an urban core. This ambiguity has made it empirically difficult to assess whether the AMM model is a useful tool for predicting patterns of location by income.

This paper utilizes Beijing's 2008 road rationing policy to empirically test whether the monocentric model can explain urban patterns of income sorting, a connection which Duranton and Puga (2015) describe as "still very much an open question." One important reason sorting predictions of the AMM model are difficult to test is that the composition of income relative to the urban core depends upon preferences for both housing and short commutes. Demand for larger housing "pushes" individuals away from the city center while demand for brief commutes "pulls" individuals back in. Because of this tension, the AMM model has met with limited success in predicting the location patterns of different income groups. LeRoy and Sonstelie (1983) extended the AMM model to explain nineteenth century cycles of gentrification and urban decline. Highlighting the role of transportation innovation, their model predicts that new transit technology that is faster but expensive (e.g., a car) relative to existing transit (e.g., a bus or walking) will induce the rich to decentralize relative to the poor.

Although this pattern is consistent with several empirical studies of US cities (Margo 1992; Gin and Sonstelie 1992; Glaeser et al. 2008; Brueckner and Rosenthal 2009; Lee and Lin 2017), the model has yet to be tested in a quasi-experimental setting. This is an important gap in our understanding of inter-city location choices. It is not clear, for instance, whether observed positive relationships between inexpensive transit access and low income households (Glaeser et al. 2008; Gin and Sonstelie 1992) are a result of unobserved demand for other location-specific amenities like public welfare services; or whether cyclical suburbanization trends of wealthy households are a direct response to changes in transit technology as the model would predict (Lee and Lin 2017; Brueckner and Rosenthal 2009).[2] Thus, establishing a causal link between transit costs, income, and location choice remains elusive.

To establish such a casual link, two components are necessary: first, a shock to transportation costs (or demand for housing); and second, a shock that impacts one income group differently than the other. We focus on the context of Beijing's 2008 road rationing policy (RRP) because it uniquely affords both components. First, the policy generated a shock to transportation costs by increasing the cost of driving by car. People who previously drove to work had to either incur large fines to drive or substitute to other modes of transit at least one day per week. Second, transit mode choice is largely

[2] Lee and Lin (2017) show that post-WWII suburbanization trends in US cities are less pronounced in cities with significant natural amenities. Brueckner and Rosenthal (2009) demonstrate that the life cycle of housing stock helps explain empirical irregularities over time in the relationship between income and urban location choice.

stratified by income group in Beijing, unlike in most US or European cities.[3] Personal automobiles are expensive relative to average income levels, and ownership is restricted to only those who can enter a lottery system and are lucky enough to win a license plate (Li, 2018). Lower income individuals generally rely on bus, subway, cycling or walking. This feature makes Beijing a particularly useful setting for testing predictions of LeRoy and Sonstelie (1983) because high income groups were more likely to be affected by the RRP than low income groups.

We motivate our empirical approach through a stylized model of urban land use following AMM and LeRoy and Sonstelie (1983). The model has two main predictions: (i) *an increase to the cost of commuting by car will increase demand for housing proximate to areas of the city where people work and areas of the city where it is easier to substitute to alternative modes of travel*, namely subway stations; and (ii) *as driving costs rise, the group formerly most likely to drive* (in our case, the rich) *will outbid other groups for those areas proximate to business districts and subway stations.*

To test these predictions, we compile a new dataset spanning 2005 through 2014 with micro-level information on over 250,000 housing transactions and demographics on over 46,000 households. For each housing unit, we calculate its proximity to central business districts and subway stations. Using this variation in proximity across housing units, we provide new estimates on the effect of driving restrictions on demand for housing as well as the composition of households near business districts and subway stations. Our experimental design relies on the exogeneity of Beijing's road rationing policy as a shock to driving costs. In a difference-in-differences design, we test whether housing units that are closer to central business districts or subway stations are in greater demand among high-income groups following the RRP as a consequence of this group's desire to maintain short commutes.

To highlight the role of income-sorting in Beijing's house price adjustments, we carry out our empirical approach in two steps. First, we leverage the exogeneity of the RRP to measure how the baseline premium paid for housing units proximate to business districts and subway stations changes as a consequence of the policy. Following Rosen (1974), we use the variation in housing prices that is explained by variation in proximity as a measure for people's demand for proximity. Second, we estimate the causal effect of the RRP on the propensity of high income groups to live closer to business districts or subway stations relative to low income groups. The experimental design considers households with different incomes, and compares differences in their distance to business districts and subway stations before relative to after the driving restriction. Our detailed data and the natural

[3] Severen (2019) shows that all income groups are equally likely to utilize LA's Metro Rail system, even after its expansion.

experiment afforded by the RRP allow us to document that income-based sorting near business districts and subway stations was an important mechanism driving housing price appreciation in these areas. In so doing, we contribute to existing work specific to Beijing's RRP (Xu et al. 2015) as well as work broadly interested in assessing the validity of the transit-based explanation for income sorting in cities (Brueckner and Rosenthal 2009; Glaeser et al. 2008).

An important component of our empirical design is that we test for post-RRP changes in bid-rent gradients and income-distance gradients *within neighborhoods* of Beijing. These fine-scale fixed effects control for time-invariant differences across neighborhoods that could otherwise predict differences in prices or differences in household income across space (such as proximity to natural amenities or high-performing schools). We also include a comprehensive set of controls for housing characteristics so that our estimates are identified off of observationally-similar households that differ only with respect to their distance from business districts or subway stations.

Despite use of neighborhood fixed effects and the availability of detailed controls, our difference-in-differences approach may be confounded by at least two factors that occurred over our period of study: first, Beijing's subway network expanded considerably.[4] Li et al. (2016) use variation in Beijing's subway expansion from 2001 to 2013 to show that property values increased by almost 1% for every 1 kilometer reduction in distance to a subway station. Second, Beijing's housing values experienced substantial appreciation during this time period. Prices grew an average of 13.6% per year, or roughly double that of the US housing market from 2000 to 2007 (U.S. Census 2019; Fang et al. 2016).[5] If Beijing's housing boom and subway expansion explain most of the change in housing prices before relative to after the RRP, our estimates of the policy effect will be spurious and will likely over-estimate the true effect.

We address these concerns in the following ways. First, we estimate hedonic and sorting effects dynamically, allowing the bid-rent and distance-income gradients to vary across time periods. This allows us to test for evidence of pre-RRP price or sorting trends. Our event studies show that the price premiums and sorting responses to subway and business district proximity increased only after the road rationing policy, suggesting that general price appreciation in the housing market does not explain our results. Second, we find the price premium following the RRP persists even for neighborhoods that had pre-existing stations. Third, areas that received new subway stations did not exhibit differential

[4]We plot the year-on-year expansion in Appendix Figure A1.

[5]We plot the mean annual price per square meter for housing among transactions within our sample in Appendix Figure A2. Holding a jiedao fixed, house prices grew an average of 13.6% per year.

income growth trends in the 2.5 years leading up to the station opening date. We interpret these findings as evidence that the post-RRP shift in the demand for subway proximity was unlikely to be driven by secular investment or gentrification trends in areas that received new subway stations.

Our analysis provides two key findings. First, we find that the RRP increased the premium for both subway station proximity and proximity to Beijing's central business districts. Our preferred estimates show that road rationing increased the price differential for a housing unit one kilometer closer to a subway station relative to a house 1 kilometer further away by approximately 3.6% (or about $3,000 for the average housing unit) compared to before the policy. Similarly, the price differential for a housing unit one kilometer closer to a central business district relative to a housing unit further away increased by 1.3% (or about $1,000 for the average housing unit) compared to before the policy. Pre-trends show that the premium for proximity is stable in the periods prior to the road rationing, but shifts significantly in the aftermath of the policy. Our results imply that the Beijing bid-rent gradient for subway proximity was twice as responsive to the road rationing policy as prior literature suggests.

Second, we find modest but statistically significant evidence that the demographic composition of households near subway stations and the business districts shifted toward higher income households over the same period as the price adjustments. These findings are consistent with our model's predictions, and underscore how income sorting was a mechanism driving up housing price growth in these same areas of the city following the RRP. Specifically, we find that the difference in distance to central business districts across two households differing in wealth by 10% increased by 0.5 percentage points (or about one-tenth of a kilometer) from a baseline difference in distance of 7.7% (or about 1.5 kilometers). In other words, if one household made twice as much income as another, the wealthier household was likely to live approximately 1 kilometer closer to the central business district after the road rationing policy. We find a similar magnitude for the sorting response near subway stations. The difference in distance to subway stations across households differing in wealth by 10% increased by 0.8 percentage points (or about one-tenth of a kilometer) from a baseline difference in distance of 9.7%.[6] Data patterns suggest these sorting results are driven by increased development and inflows of high income households as opposed to displacement of incumbent lower income households. These findings are the first to demonstrate that driving restriction policies, aside from impacting the housing market,

[6] We translate 0.5 pp (0.8pp) into one-tenth of a kilometer based on the mean pre-RRP distance to a central business district (subway) in our sample of 20.4 km (15.2km). We calculate the baseline difference in distance of 7.7% (9.7%) from a cross sectional regression of ln(Distance to CBD) (ln(Distance to Subway)) as a function of ln(household income) with year-by-month fixed effects.

can additional impact the composition of income near transit accessible areas. Specifically, we find that lower income households are less likely to move into transit accessible areas relative to before the road rationing policy.

Our paper makes contributions to prior literature that are of theoretical and empirical consequence. We begin by discussing the theroetical contributions. The monocentric city model dominates much theoretical work on urban spatial structure, however empirical support for its main prediction —a negative relationship between house prices per unit and distance from an urban core —is somewhat mixed (Duranton and Puga 2015). McMillen (2006) discusses how unobserved differences in housing quality, like proximity to public services, can lead to estimates of the bid-rent gradient that appear contradictory to theory. A key contribution of our paper is that we utilize the RRP to estimate a *change* in the house price-distance and a *change* in the distance-income gradient as opposed to a level estimates of these gradients. The natural experiment of the RRP allows us to overcome some of the empirical difficulties found in prior literature by holding unobserved amenities fixed. Our paper provides robust evidence in support of the monocentric city model predictions that bid-rent gradients become steeper as travel costs increase.

Furthermore, our investigation provides empirical contributions to prior studies concerned with the positive relationships between inter-city location choices among the poor as a function of public infrastructure access (Brueckner et al. 1999; Baum-Snow and Kahn 2000; Glaeser et al. 2008; Brueckner and Rosenthal 2009).[7] Our hedonic analysis of subway proximity fits into a large body of literature that demonstrates train and subway access capitalize positively into housing prices.[8] Redding and Turner (2015) provide a comprehensive review of this literature. Most of this literature relies on subway or transit network *expansion* to infer valuation of access (Gibbons and Machin 2005; Billings 2011; Li et al. 2016; Ahlfeldt and Wendland 2011; Tsivanidis 2019; Severen 2019). In contrast, our hedonic estimates can inform the optimal provision of transit technology when private vehicle use is *restricted*—a scenario increasingly prevalent among the world's largest cities.

Our paper is most similar to Xu et al. (2015), which finds that prices for housing near subway

[7] More broadly, our paper contributes to a large literature on the role of public goods in determining house prices and residential location decisions. For example: Koster and Rouwendal (2017) shows that property values increase following public investment in historic amenities; Chay and Greenstone (2005) and Bayer et al. (2009) study the impacts of federal air quality improvements on housing values and gentrification; while Black (1999) and Cellini et al. (2010) study public school quality.

[8] Manelici (2017) provides a notable exception to this using exposure to terrorist attacks. After the 2005 London subway bombings, she finds that price of housing within 600 meters of London's subway stations fell by 6% relative to housing further from stations for up to a year after the attacks.

stations increased in the six months following Beijing's road rationing. We extend their study to examine underlying household sorting and changes in the spatial distribution of residential wealth due to the policy. In general, our results underscore the importance of transportation infrastructure and transit technology as a determinant of urban spatial structure. While investment in transit infrastructure has been shown to attract the poor (Glaeser et al. 2008) to public transit and the city center, we demonstrate that increasing commute costs for the wealthy can actually disperse the poor as they are outbid by the rich in these areas.

2 Background and Data Description

In this section, we provide background information on Beijing's road rationing and discuss data sources and sampling restrictions.

2.1 Road Rationing in Beijing

Beijing's road rationing policy went through several iterations between 2008 and 2011, generally leading to more lenient restrictions. Government officials first announced the policy in June of 2008 as a temporary restriction that would extend through the Olympic and Paralympic Games from late July to late September 2008. Initially, private vehicle owners could only drive their vehicles within the city every other day based on an odd-even schedule. The policy was enforced seven days a week nearly all day, except for three hours from midnight to 3am. At the end of this temporary restriction, the government decided to continue with the policy through April of 2009.

In its second phase, the policy relaxed its restriction on vehicle use to one day per week within (and including) the Fifth Ring Road during week days from 6am until 9pm. A driver's restricted day was based on the last digit of their vehicle's license plate number. A driver's relevant restricted day would rotate every four weeks. When this half-year trial ended, the government, again, announced an extension of the policy through April of 2020. This new policy restricted car use within, but excluding the Fifth Ring Road, rotated restricted days every 13 weeks, and reduced the restricted hours from 7am to 8pm. This final iteration of the policy still stands today. Buses, taxis, and public-use vehicles for the police and military are not affected by the restriction (Viard and Fu 2015).

Viard and Fu (2015) found that Beijing's road rationing reduced particulate matter (PM_{10}) by 21%, with strong compliance and little evidence of inter-temporal substitution (i.e., driving more during non-restricted hours) or an increase in total number of vehicles in circulation, as in Davis (2008). In Beijing, it is difficult to evade detection because cameras throughout the city (as opposed

to police) monitor the plates on vehicles. If an individual violates the restriction, they are fined 300 yuan (or about $40) per violation. These fines repeat every three hours, allowing some grace period for drivers to leave the roadway if they drive on a restricted day. Precise statistics on the total number of violations that have occurred are difficult to find, however anecdote suggests that the probability of receiving a fine on a restricted day is between 20 and 40%. Beijing further restricts people's ability to purchase a second car, and purchase of a first car is regulated by a lottery system. The limited scope for noncompliance or substituting behavior were key to the success of Beijing's RRP in improving air quality.

Transit mode choice is stratified by income in Beijing. While we do not observe transit mode choice among the home buyers in our data, aggregated statistics on mode choice by income group from the 2010 Beijing Household Travel Survey (Beijing Transport Institute 2010) supports our prediction that the RRP binds mainly for the wealthy who can afford cars. Figure 2 plots the distribution of mode choice by income group as of 2010. Nearly 40% of earners in the top income bracket relied on cars to commute to work, while less than 20% of earners in the bottom income brackets relied on cars to commute. For public transit, just 14% of the top earners relied on public transit (subway or bus), whereas 20-21% of individuals in the bottom income bracket chose to commute by subway or bus. Although subway transit fares are heavily subsidized by the Beijing government at about $0.30 per trip,[9] walking and biking are the dominant modes of commute among most lower income groups (Beijing Transport Institute 2010).[10] Research by Gu et al. (2017) uses the 2010 travel survey and shows that wealthier commuters were twice as likely to switch from auto use to an alternative mode on restricted days compared to lower income groups who rely on public transit, biking or walking.

2.2 Data Sources & Description

Our empirical analysis requires information on housing prices, residential locations, and household income. We assembled this information using individual real estate transactions sourced from two major Beijing real estate firms, as well as mortgage loan applications sourced from an anonymous government-backed mortgage provider.[11] The real estate transaction data comprise approximately

[9] Fares became distance-based after 2014, however trips within the 4th Ring Road (under 22 kilometers) were still relatively cheap, averaging about 5 yuan per trip.

[10] Chu et al. (2019) use entry of bike sharing programs in 10 major Chinese cities as a natural experiment in a cross-city hedonic analysis. They find suggestive evidence that bikes serve as a complement to subway use by solving the "last mile problem."

[11] The anonymous mortgage provider operates as a government-backed credit market to encourage home ownership especially for low- and middle-income households. In the absence of a developed credit market, people can access loans through their employers (Tang and Coulson 2017). At participating employment firms, each employee and his/her employer have to contribute a specific percentage of his/her monthly salary to the government-backed mortgage

17% of all housing purchases within Beijing from 2006 through 2012. Our sample of mortgage contracts comprises the majority of the mortgage market in Beijing during the sample period, though the precise market share is difficult to quantify because mortgage loans made to individuals not participating in the government-backed loan program (e.g., individuals at non-salaried jobs, individuals working part-time or unemployed, or the very wealthy) are not represented in our data.

Each housing transaction contains the sale or rental price as well as descriptive information on the housing unit (including number of bedrooms, floor level, decoration level, types of appliances, etc.) and information on the housing complex (including geographic location, total size, parking availability, green space, proximity to key schools, etc.). The mortgage loan data also provide information on housing unit price and descriptive information on the housing complex building. Importantly, the mortgage data provide detailed information on the loan applicant's demographic characteristics, including their income, education levels, and place of employment.

Figure 3 shows the spatial distribution of our sample of housing units throughout Beijing. Housing units are concentrated near the city center and near subway lines shown radiating outward from the Second Ring Road. Beijing is divided into 18 districts indicated by the thick green lines, each of which contains several smaller neighborhoods. The real estate transaction data identifies the "jiedao" of a housing unit, whereas the mortgage loan application data identifies the zip code of a housing unit. Jiedao are administrative units similar to a census tract, whereas zip codes are used for mailing addresses. They are similar in size: each district of Beijing contains an average of 35 jiedao and 32 zip codes. The median area of a jiedao in our sample is approximately 1.65 square miles. Throughout this paper, we refer to jiedao and zip codes collectively as "neighborhoods," however our estimation strategies define unique fixed effects for each level of geographic organization.

Figure 4 shows the location of Beijing's major employment centers. Like many major cities, Beijing does not have one singular central business district, but several subcenters.[12] The city's geographic center is a cultural and consumer-oriented district that, itself, is surrounded by several business

account. The employees can then obtain a mortgage loan with a subsidized interest rate for home purchase, which is about 1.5 percentage points, or nearly 30%, lower than the commercial banks' mortgage rate. Virtually all eligible home buyers apply for this mortgage first before going to other sources of funding. The data cover the universe of all home purchases in Beijing that made use of a government-backed mortgage loan from 2006 to 2013. Mortgage refinancing is uncommon in China, and there are no refinancing observations in the sample. As a result, each mortgage contract refers to a housing transaction.

[12] While the economic literature on urban spatial structure often assumes cities are circular or radially symmetric, a growing literature has acknowledged the polycentric structure of cities (e.g., Anas et al. 1998; Lucas and Rossi-Hansberg 2002; Harari 2016). Lucas and Rossi-Hansberg (2002) shows that negative bid-rent gradients toward an urban core will theoretically arise even in a city with an initial uniform distribution of employment.

district clusters. These clusters, like the "Financial District" (Xicheng) or the "Commercial District" (Wangujing), contain most of the employment in Beijing. For this reason, we define the Beijing "central business district" (CBD) as a relative measure and assign the closest major employment center as a given housing unit's CBD. Our results are generally insensitive to alternative definitions of Beijing's CBD, as demonstrated in Section 5.1.

Our identification strategy exploits variation in the housing price-distance gradient before and after the road rationing policy within a neighborhood of Beijing. Figure 5 demonstrates our within-neighborhood variation. The jiedao are outlined by the thick black lines. Among our data sample, each jiedao experienced an average of 802 transactions while each zip code experienced an average of 194 mortgage loan applications. We restrict our analysis to housing units within the Sixth Ring Road of Beijing which skews the sample of neighborhoods toward those with smaller square areas.[13] Our sample covers roughly two-thirds of the 300 jiedao within Beijing and over 90% of the 200 zip codes.

Table 1 provides summary statistics on a subset of the variables available within each of our datasets. The purchase price varies considerably more in the real estate data than in the mortgage dataset. The mortgage data housing units are also further from the city center and further from subway stations, on average. This is partially due to the selection of individuals represented by the mortgage data, which overrepresent the middle class demographic. Home buyers able to utilize the government-backed mortgage loan system are less likely to be entrepreneurs or wealthy households.

The Beijing government enacted several city-wide policies after 2011 that likely impacted the housing market and demand for automobiles.[14] Our main specifications use the transactions occurring between July 2006 and July 2010 that predate some of these policies to mitigate correlations from potential confounding policies. The year-on-year frequency of transactions in our real estate sample correlates closely with Beijing's housing market (shown in Appendix Figure A4). Beijing's housing market contracted during the 2008 global recession. At the end of 2008, the Chinese government implemented a series of aggressive housing market policies, including lowering mortgage interest rates and down payment requirements, which led to a massive rebound in 2009. In April of 2010, Beijing's local government implemented housing market cooling measures to avoid a speculation-driven housing

[13] Appendix Figure A5 shows the cumulative distribution of jiedao size within our sample compared to that of the Beijing population.

[14] For example, in January 2012 the government implemented a lottery system for purchases of automobile license plates in order to limit the total vehicle fleet on Beijing's roadways (see Lu (2018) for an analysis of the license plate restriction on Beijing's housing market). In April of 2011, the government enacted an anti-speculative policy that restricted home purchases for natives, and prohibited home purchases for non-natives of Beijing (see Sun et al. (2017) for analysis of the home purchase restriction on Beijing's housing market).

bubble, including increasing the minimum down payment required for purchasing a second home and subsidizing construction of affordable housing. These anti-inflationary policies remained in place through 2014, which is why the transaction volume never reached the 2009 level.

3 Theoretical Framework

We predict how a city-wide road rationing policy will affect the sorting of low relative to high income individuals through the stylized AMM monocentric city model, and its extension by LeRoy and Sonstelie (1983). We then discuss application of our model to Beijing's road rationing policy and explore relevant data patterns across house prices, proximity, and household income.

3.1 Residential Equilibrium & the Bid-Rent Function

Consider a monocentric city with a central business district (CBD) where all residents supply work at wage w to earn y income. Residents live outside the CBD in the residential district of the city. Commute time increases monotonically with distance from the CBD. There are two possible modes of traveling to work: car or subway. Consumers decide where to live, choosing a pair of location parameters (x, δ) where x is the distance from the CBD to an individual's residence and δ is the distance from an individual's residence to the nearest subway station. Consumers choose the pair (x, δ) so as to maximize consumption of housing h with price p and the numeraire good z with price one. Individuals commute distance x if they commute via car and distance $(x + \delta)$ if they commute via subway. Transit time is denoted as $T(n, x, \delta)$ and is a function of distance to CBD x, distance to the nearest station δ, and the likelihood of commuting via subway n. Discussed in greater detail below, n can vary with commuter type (rich versus poor) and the existence of road rationing days. The monetary time-cost of commuting is $w \cdot T(n, x, \delta)$.[15]

Our empirical approach focuses on price and sorting effects over a relatively short time horizon of two to four years, consequently we assume that the city boundary is fixed, housing supply is fixed, and the city is closed, without in or out migration. Residents face the following maximization problem where they maximize consumption of housing and the numeraire good subject to their budget constraint:

[15] Realistically, commuting costs will include pecuniary costs like tickets for a subway or gas for a car in addition to time costs. For tractability, we model urban land use as dependent on time costs, however including these pecuniary costs in $T(n, x, \delta)$ does not alter the baseline model predictions as long as commuting costs are linear in distance (Duranton and Puga 2015).

$$\max_{z,h} U(z,h) \text{ s.t.}$$

$$z + ph + w \cdot T(n,x,\delta) = y$$

The time-cost of commuting $w \cdot T(n,x,\delta)$ reduces income because residents forgo wage earnings by allocating part of their time each day commuting. For simplicity, assume that there are two modes of transit, car or subway. Transit time $T(n,x,\delta)$ from any distance x to the CBD depends upon the transit mode and the speed of the transit mode. Driving transit time is x/ν, where ν is driving speed. Subway transit time includes two components. First, walking time to the subway station δ divided by walking speed ω; and second, time on the subway to the CBD, x/σ, where σ is subway speed. Together, total transit time via subway is $\frac{\delta}{\omega} + \frac{x}{\sigma}$. For any x, we assume driving is a faster mode of transit than taking the subway: $\frac{x}{\nu} < (\frac{\delta}{\omega} + \frac{x}{\sigma})$. We define transit time as follows:

$$T(n,x,\delta) = n\Big[\frac{\delta}{\omega} + \frac{x}{\sigma}\Big] + (1-n)\frac{x}{\nu} \tag{1}$$

In equilibrium, each resident has achieved their highest utility subject to their budget constraint; and all residents i must have equal utility levels: $\max_{z,h} u_i = \bar{u} \forall i$. Solving this system of equations, we have the condition that each resident chooses a housing location (x,δ) such that:

$$\frac{\partial p}{\partial x} = -\Big[\frac{n}{\sigma} + \frac{1-n}{\nu}\Big]\frac{w}{h} \qquad \text{and} \tag{2}$$

$$\frac{\partial p}{\partial \delta} = -\Big[\frac{n}{\omega}\Big]\frac{w}{h} \tag{3}$$

In Appendix B, we show the derivation of Eq. 2 in greater detail. Eq. 2 shows that price of housing falls with distance enough to compensate individuals for their longer commutes. This is the spatial equilibrium condition that is the basis of the monocentric city model. Ex ante, both choice of x and δ matter for individuals commuting via subway, but only the choice of x matters for individuals commuting via car. Eq. 2 describes the bid-rent for distance from the CBD, holding δ constant, whereas Eq. 3 describes the bid-rent for distance from a subway station holding x constant.

3.2 Heterogeneity by Mode Choice

Groups facing different preferences for housing consumption h and time costs $w \cdot T(n,x,\delta)$ will have distinct bid-rent gradients. LeRoy and Sonstelie (1983) develop the case where a high-income group, possessing greater opportunity cost of time, commute via car. Cars are more expensive but a faster transit mode relative to public transit. The poor rely on public transit since it is not economical for them to commute via car. This setting is quite applicable to Beijing where wealthier people use cars and the lower income rely on public transit. Following LeRoy and Sonstelie (1983), assume there

are two consumer types i: rich and poor. Each consumer type will differ in their wage, housing consumption, and likelihood of commuting via subway. We introduce an index i for each of these variables (w_i, h_i, n_i) where $i = p, r$. Subscript p denotes the housing consumption, wage, and transit mode of the poor and r the same for the rich. For the poor, n_p approximates 1 because the poor are very likely to rely on subway transit. The rich rely on cars, but the rich may use either mode depending on effective road rationing days, thus: $0 \leq n_r < n_p \sim 1$.

Rearranging Eq. 2, the poorer group will have a steeper bid-rent gradient than the rich and, therefore, live closer to the city center if and only if:

$$\begin{aligned} \frac{h_r}{h_p} > \frac{\partial T(n_r, x, \delta)/\partial x}{\partial T(n_p, x, \delta)/\partial x} \times \frac{w_r}{w_p} &= \frac{n_r/\sigma + (1-n_r)/\nu}{n_p/\sigma + (1-n_p)/\nu} \times \frac{w_r}{w_p} \\ &\approx \frac{n_r/\sigma + (1-n_r)/\nu}{1/\sigma} \times \frac{w_r}{w_p} \end{aligned} \tag{4}$$

Beijing's road rationing, operationalized by an increase in n_r, serves to change the ratio of transit time costs for the rich car users relative to the poorer subway users. As the road rationing pushes a rich resident to utilize the subway, the ratio $\frac{n_r/\sigma+(1-n_r)/\nu}{1/\sigma}$ moves closer to parity, and thus Eq. 4 is *less* likely to hold following Beijing's road rationing. This logic tells us that higher-income individuals will find housing close to the city center more attractive, and will consequently move closer to the city center following the road rationing.

Similarly, poor households will live closer to subway stations, conditional on x, if Eq. 3 is steeper for the poor relative to that of the rich:

$$\frac{h_r}{h_p} > \frac{w_r}{w_p}\frac{n_r}{n_p} \tag{5}$$

As n_r increases, the road rationing makes Eq. 5 less likely to hold. Collectively, this logic tells us that higher-income individuals will move closer to the CBD and closer to subway stations, conditional on location x, following the city-wide road rationing.

3.3 Application to Beijing's Road Rationing Policy

An advantage of our setting is that we isolate *shifts* to the bid-rent gradients $\frac{\partial p}{\partial x}$ in Eq. 2 or $\frac{\partial p}{\partial \delta}$ in Eq. 3, as opposed to their actual slopes. Beijing's road rationing policy served to *shift* both gradients. Consequently, we can identify plausibly exogenous changes to the bid rent and changes in demographic composition through estimating the second derivative of both equations with respect to n as follows:

$$\frac{\partial^2 p}{\partial x \partial n} = -\frac{w}{h}\left[\frac{1}{\sigma} - \frac{1}{\nu}\right] \tag{6}$$

and

$$\frac{\partial^2 p}{\partial \delta \partial n} = -\frac{w}{h}\frac{1}{\omega} \tag{7}$$

Eq. 6 provides the rate of change in the price versus distance-to-city-center trade off, all else equal, following the road rationing policy. Similarly, Eq. 7 provides the rate of change in price versus distance-to-subway station trade off, all else equal, following the road rationing policy. Our empirical approach will estimate changes in both bid-rent gradients, and then test predictions of the model on sorting of lower relative to higher income households near the CBD following Eq. 4 and subway stations following Eq. 5.

3.4 Preliminary Evidence

We show preliminary evidence that the bid-rent gradients have shifted over time based on the raw data. Figure 6 plots the bid-rent gradients before and after the road rationing policy. The difference in slopes shown in these figures are, respectively, estimates of Eq. 6 for the price-distance to CBD gradient and Eq. 7 for the price-distance to subway gradient. The price premium per square meter for subway access clearly increases following the road rationing policy in Panel B. The premium for access to the CBD in Panel A is less striking, but still demonstrates a slight tilt from the pre-RRP period. These price dynamics are intuitive if both the rich and poor are competing for housing proximate to subway stations, but less so for proximity to the CBD. The poor are not impacted by the road rationing, thus do not compete for housing close to the city center. Both rich and poor, however, prefer housing closer to subway stations, all else equal.

Figure 7 shows the relationship between income and distance to the CBD in Panel A and the nearest subway station in Panel B, respectively. The decentralization of the lower-income relative to the higher-income is prevalent in the raw data. Both gradients have become steeper over time, particularly for subway proximity. In the post driving restriction period, Beijing appears similar to older US and European cities in its demographic spatial structure as average income declines with distance from the CBD (Brueckner et al. 1999). However, these patterns are a marked shift from the pre-driving restriction period, when the relationship between income and CBD proximity was weaker. Noticeably in Panel B, mean distance to a subway station fell over time for all income groups as they system expanded.[16]

4 Empirical Approach

The goal of our empirical approach is to estimate how Beijing's RRP affected, first, the premium for proximity to subway stations and central business districts; and second, the residential location choices

[16] Appendix Figure A6 and A7 plot the distance-income gradient and price-distance gradients, respectively, for alternative definitions of Beijing's CBD. In nearly all cases, the post-period gradient becomes steeper.

of low- relative to high- income households. We first explore how Beijing's transit policies impact demand for housing near the city's central business districts and subway stations. The residential locations of the rich relative to the poor will be driven by changes in their willingness to pay for proximity.

Let i index housing units, j index jiedao,[17] t index the day of a transaction, and q index one of 28 quarters from 2005 to 2011. We estimate the effect of the RRP on the distance-to-subway (and distance-to-CBD) price premium through the following event study specification:

$$\ln(p_{ijt}) = \sum_{q=1(\ni 15)}^{28} \kappa_q (Km_{it} \times D_q) + \alpha Km_{it} + \mathbf{X_{ijt}}\theta + \gamma_j + \tau + \varepsilon_{ijt} \tag{8}$$

where p is the price of housing per square meter, Km_{it} measures the distance to the nearest subway station or business district, and D_q is a quarter dummy. $\mathbf{X_{ijt}}$ controls for housing unit and building complex attributes and γ_j and τ are jiedao and time fixed effects, respectively. These fixed effects remove confounding unobserved differences in amenities across Beijing neighborhoods, such as the existence of high quality shops in the central Xidan district or proximity to premiere universities in the northwest Haidian district. τ includes year and month fixed effects in our main specification, but we apply finer-scale time fixed effects in various specifications. The parameters κ_q measure the difference in the housing price-distance gradient in quarter q relative to the baseline, the third quarter of 2008, which is quarter 15 in our sample.[18] We cluster standard errors ε_{ijt} at the jiedao level. We estimate the coefficients of interest, κ_q using variation in CBD and subway proximity *within* a jiedao. The relevant variation that identifies κ_q differs slightly across the CBD distance hedonic regressions versus the subway distance hedonic regressions. Distance to the nearest CBD does not vary over time for a given housing unit. Consequently, for specifications where Km_{it} measures distance to the nearest CBD, κ_q is identified off of cross-sectional variation within a jiedao. In contrast, for specifications where Km_{it} measures the distance to the nearest subway station, parameters κ_q are also identified off of time-wise variation in subway proximity. This is because Beijing's subway system expanded during our time period of interest, thus some housing units became closer to the nearest subway station over time. As a robustness check in Section 5.4, we restrict our subway distance hedonic regressions to housing units that do not vary in their proximity to the nearest subway station. Our conclusions remain the same whether or not we identify the hedonic parameter off of housing units that become closer to stations over time.

[17] Jiedao is a neighborhood that usually contains several apartment complex on a street or street segment. In our sample, a Jiedao has an area of approximately 1.65 square miles

[18] We choose a log-linear specification for ease of interpretation, however we show in Appendix Table A2 that our results are robust to a log-log specification used in Xu et al. (2015).

The key to our empirical approach is that we estimate *shifts* in the price-distance gradient; and distance-income gradient caused by the driving restriction rather than the gradients' absolute slopes $\frac{\partial p}{\partial x}$ in Eq. 2 or $\frac{\partial p}{\partial \delta}$ in Eq. 3. Several factors can confound empirical estimates of these slopes, such as proximity to high quality schools or proximity to recreational amenities (i.e., parks or restaurants). Omission of such unobserved factors will bias the price-distance gradients, either downward in the case of positive correlation of proximity and desirable amenities; or upward in the case of a proximity and dis-amenities, such as the prevalence of noise and congestion near the city center or subway stations.[19] While spatial fixed effects can correct for some of the omitted variable bias, there is a tradeoff between employing fixed effects at a fine-enough scale to remove all spatially-dependent amenity variation, and identification of the bid-rent gradient. Beijing's RRP served to *shift* these gradients. By exploiting this plausibly exogenous policy change, we can identify a causal impact of the driving restriction on proximity premiums without assuming that neighborhood-level amenities and housing prices are independent. Rather, our underlying assumption to identify a causal effect of the driving restriction is that prices would have trended in parallel for observationally similar housing units within the same neighborhood in absence of the RRP.

In our model, house prices adjust as a result of higher income groups outbidding lower income groups for proximate locations. Inequalities in Eqs. 4 and 5 provide conditions for lower income groups to live closer to the city center and near subway stations, respectively. These conditions are *less* likely to hold following the RRP if the rich increase their use of the subway relative to the poor; that is if the ratio n_r/n_p increases. We predict n_r will increase relative to n_p following the RRP because, as shown in Figure 2, wealthier income groups utilize private vehicles to commute more than lower income groups. The driving restriction will require that wealthier commuters adjust their commute mode choice away from driving toward public transit. In contrast, lower income households will be less directly affected by the policy since they are the incumbent public transit users. As the ratio n_r/n_p increases, our model predicts that the average income in areas proximate to subway stations and business districts will increase.

To test predictions of our model, we employ data on household income, demographics, and location from the mortgage application data. We estimate the relationship between household income and proximity over 28 quarters spanning the RRP policy from 2005 through 2011 in a flexible event

[19] Beijing's subway network is entirely underground, thus the infrastructure itself does not alter the visual appeal of a particular location. However, there may be some dis-amenity from living directly beside a subway station due to heavier foot traffic or noise.

study specification:

$$\ln(Km_{izt}) = \sum_{q=1(\ni 15)}^{28} \alpha_q(\ln I_{izt} \times D_q) + \psi \ln I_{izt} + \mathbf{Z}_{izt}\theta + \zeta_z + \tau + \mu_{izt} \tag{9}$$

where i indexes housing units (equivalently households), z indexes zip codes, t indexes the day of a mortgage application, and q indexes one of 28 quarters. Km_{izt} is the distance from housing unit i to the nearest subway station or business district, I_{izt} is the monthly household income for the primary and secondary earners purchasing housing unit i at time t, and D is, as before, a series of indicator variables equal to one for each quarter from 2005 through 2011. The vector $\mathbf{Z}$ includes controls for housing unit attributes and characteristics of the primary and secondary earners of the household including age, education level, work tenure, employer industry type, and position rank. These demographic controls remove potential sorting responses due to unobserved changes to labor demand or changes to the location of employers. $\mathbf{Z}$ also includes controls for distance to the nearest subway station in the CBD sorting regressions; and distance to the nearest CBD in the subway station regression. The fixed effects ζ_z and τ control for time-invariant characteristics of housing location i and macro-economic trends effecting all housing units, respectively. In our main specification τ includes year and month fixed effects. α_q provides the elasticity of distance with respect to income in quarter q relative to the third quarter of 2008, quarter 15 in our sample. We cluster standard errors μ_{izt} at the zip code level.

4.1 Identification Challenges

Our empirical approach is subject to two main threats to identification of κ_q in Eq. 8 and α_q in Eq. 9. The first one is unobservables that could have changed at the time of the policy and also affect the outcome variables (prices or location choices). That is, price changes could have occurred absent the road rationing policy if areas near CBD and subway stations were on a differential growth trajectory relative to the areas far from CBD and subway stations. For instance, if dining, shopping, and entertainment establishments grew over time in the same areas as subway stations and CBDs, then bid-rent gradients could have become steeper over time due to growth in these amenities, as opposed to the road rationing policy. If these correlated time-varying trends capitalized positively into housing prices, an ordinary least squares (OLS) estimate of κ_q in Eq. 8 would over-estimate the effect of the road rationing. If, however, correlated time-varying trends are "bads", like noise and congestion rather than the aforementioned "goods", an OLS estimate of κ_q would under-estimate the effect of the road rationing.

Similarly, OLS would not provide a consistent estimate for α_q in Eq. 9 if mean proximity to

CBDs or subway stations would have increased for higher income households absent the road rationing policy. In other words, if amenities like high quality shopping and dining grew over time near subway stations or CBDs, and these types of amenities disproportionately attract higher income individuals, then the composition of income near these areas would have increased regardless of the road rationing policy.

The identifying assumption is that housing prices and location choices would have trended similarly with respect to their distances to subways and CBDs in absence of the road rationing policy. We can test the plausibility of this assumption by examining trends in the price-distance or distance-income gradients in quarters leading up to the road rationing policy. If the difference in price or income between proximate and far housing units is stable in periods leading up to the RRP, it is likely that the such differences would have remained stable in absence of the RRP. To test these assumptions, we present dynamic effects specifications that allow for the treatment effects of proximity on prices, and income on distance to flexibly vary over time. With this approach, we are agnostic as to the start date of the RRP. We test, for instance, whether news coverage of the driving restriction in early 2008 (Hooker 2008) generated a response in the housing market prior to the policy's start date. The dynamic effects specification also allows us to visually examine if amenities (or dis-amenities) have grown near CBD or subway stations over time, and if these are capitalized into housing prices prior to start of the RRP in July of 2008. We further address this identification threat by including controls for district–specific linear time trends, as well as specifications with year-by-month fixed effects. Since some districts contain more stations and are closer to CBDs than others, these controls will remove unobserved growth (or decline) in proximity-correlated amenities that may impact prices or sorting.

The second main threat to identification is reverse causality. That is, proximity to CBDs or subways could have changed *as a consequence of* housing price or income growth over our time period. In this paper, we assign central business district centroids as static points that are unchanging over time by construction. Consequently, it is not possible in our setting for the location of CBDs to dynamically respond to gentrification patterns. Beijing's subway network, however, was growing over this time period, with additional lines and additional subway stops. If subway stations were sited in areas where house prices were expected to increase, or areas where the average income of residents was expected to increase, we would not be able to interpret our results as consequences of the road rationing policy. Li et al. (2016) argue that transportation planning in Beijing is largely disjoint from development and land-use planning. Nonetheless, we empirically test for possible siting endogeneity

in several ways, including testing whether subway stations opened in gentrifying neighborhoods, re-estimating our hedonic analyses excluding areas of the city where new subway stations opened, and testing for price growth trends in areas that received subway stations outside of our study period. Each of these robustness checks are described in greater detail in section 5.4. In general, we do not find evidence that new subway stations were more likely to open in gentryfing neighborhoods of Beijing.

5 Empirical Results

We now present evidence on the connection between housing demand and transit policies in Beijing. The road rationing policy increased transit costs for drivers. Our model, following LeRoy and Sonstelie (1983) predicts that changes in n_r - the likelihood of commuting via subway for the rich - should shift the price-distance gradient as well as the residential location choices of those formerly relying on personal car travel relative to those relying on public transit.

5.1 Road Rationing and Property Values

First, we test the assumption that housing prices for proximate relative to distant housing units would exhibit common trends absent the road rationing policy. Figure 8 shows estimation results of Eq. 8, the event study of the CBD housing price premium. Prior to the road rationing, the price premium for CBD proximity is not significantly different from the road rationing quarter. There is a small increase of about 1% in the premium for proximity to the CBD following the road rationing, although each individual time-specific point estimates are often statistically insignificantly, likely an issue of sample size.

Regression results in Table 2 show that CBD proximity commands between 1.3 and 1.9% (or between \$1,100 and \$1,600) higher price per kilometer after the road rationing. The use of jiedao fixed effects in column (2) significantly increases the magnitude of the policy effect, implying unobserved dis-amenities can attenuate estimates of the price-distance to CBD gradient. The jiedao fixed effects also serve to absorb nearly all cross-section variation between kilometers to CBD and price. Column (4) uses year-by-month fixed effects, such that variation is driven by transactions within the month of July 2008. In column (5), we apply controls for district-specific linear time trends to account for district-level growth that may be spatially correlated with subway proximity. The point estimate is stable across these various specifications. In Appendix Table A1, we show estimates of the post-RRP shift in price-distance gradient under alternative CBD definitions. Using our preferred specification with jiedao and year-by-month fixed effects, these alternative CBD estimates are closer to 1%, but

within the range of our main result of 1.3% where distance to CBD is the distance to a housing unit's nearest CBD. In Table 2 column (6), we add over 2,000 fixed effects for housing unit building complex. Housing units within the same building complex have the same distance to the nearest business district, consequently the identifying variation in column (6) comes only from changes over time in the premium for proximity holding the distance x fixed. The building complex fixed effects diminish the point estimate considerably. Thus, while housing units at different distances from the CBD within a jiedao exhibit differential price growth trends after the RRP, the same is not true for housing units at the same distance from a CBD.

We next consider the effect of the road rationing policy on demand for living close to a subway station. Figure 9 shows estimates of κ_q from Eq. 8 where Km is distance to the nearest subway station. The price per square meter across housing unit that differ in their distance to the subway network did not vary significantly in the time periods leading up to the road rationing policy. However, starting in the first quarter following the RRP in July of 2008, the discount (premium) for subway distance (proximity) decreased (increased) by approximately 4% per kilometer. Around April of 2011, there is an additional decrease (uptick) on the price discount (premium), which corresponds to a substantial restriction in the government's circulation of license plates and a lower likelihood of winning the license plate lottery (Li 2018).

Our regression estimates reaffirm that the price-distance to subway gradient became steeper following the road rationing policy. Results are robust to alternative controls, and finer time-location fixed effects. In Table 3, subway distance (proximity) ("Km to Subway") commands a 1% to 5% price discount (premium) per kilometer prior to the RRP policy. This level estimate may be biased if stations are sited endogenously, however we interpret the positive sign as consistent with subway distance (access) being undesirable (valuable) to city residents, all else equal. The interacted term shows that after the road rationing policy, housing units one kilometer further from a subway station sell for approximately 4% (or about $3,000) less than a comparable housing unit one kilometer closer to a subway station. The effect attenuates slightly to 2.6% after using building complex fixed effects in column (6). Even with these fixed effects, demand for subway proximity increases over $2,000 per kilometer, or double that of pre-RRP levels.

The city-wide road rationing policy increases the premium for subway access only within walking distance of subway stations. Figure 10 displays the non-parametric relationship between subway proximity and price following the RRP by plotting the mean price change for each half-kilometer bin

relative to housing units outside of five kilometers from subway stations. The premium falls to zero after approximately three kilometers, or about 1.8 miles. Intuitively, subway proximity has no impact on housing prices outside of a reasonable walking distance from the station. Figures 10 supports our interpretation that demand for the subway network—as opposed to correlated, unobserved amenities—is the mechanism driving the price premium for proximity following the 2008 road rationing policy.

We assess the magnitude of our results using a back-of-envelope value of time calculation. The magnitudes of our price premium results are between 22 and 68% of the hourly wage, based on the CBD proximity premium and the subway proximity premium, respectively.[20] These magnitudes seem plausible, considering prior literature generally finds a value of time-to-wage ratio of about 50% (Small 2012).

Our results show that subway station access came to be in much higher demand relative to CBD access following the road rationing policy. Expansion of the subway network makes transit-oriented housing locations more desirable for all marginal subway riders. However, the road rationing policy makes housing closer to the CBD more desirable only for marginal drivers with a high value of time. Those wealthy enough to drive their cars are a relatively smaller portion of Beijing's population compared to those reliant on public transit, thus it is not surprising that the subway price effect is much stronger than the CBD price effect. Both results, however, are consistent with the LeRoy and Sonstelie (1983) prediction that changes to transit costs will alter the price-distance gradient.

5.2 Comparison of the Road Rationing Price Effect with Prior Work

Our estimates of the price-distance to subway gradient are significantly larger than those of Xu et al. (2015), who find that the elasticity of price with respect to subway distance is -0.02%. We compare results directly in Appendix Table A2, where we employ the same 6-month time period, log-log specification, and start date for the RRP (October 11, 2008) as in Xu et al. (2015). Following Xu et al. (2015), we also exclude housing units located near newly-built subway stations, leaving approximately

[20] We calculate hours saved by moving one kilometer closer to either the CBD or a subway station as follows: walking speed of 15 min/km × 2 walks per day × 1 driving restricted day per week × 50 working weeks per year × 2 commuters per household × a 20-year housing tenure ÷ 60 min/hour = 1,000 total hours saved per household by moving 1km closer. Hedonic results in Tables 2 and 3 suggest the mean increase in purchase price for a housing unit 1 km closer to the CBD and subway was about $1,000 (6,800 yuan) and $3,000 (20,400 yuan) per kilometer, respectively. Dividing these premiums by the 1,000 hours saved gives an implied value of time of $3 (20.4 yuan) and $1 (6.8 yuan) per hour. As of 2007, the average resident in our sample living within 5 km of either the CBD or a subway station with non-zero income earned approximately 6,000 yuan per month, or about 30 yuan per hour (assuming they work 200 hours per month). Consequently, our hedonic CBD and subway estimates are about 22% and 68%, respectively, of the hourly wage in our sample.

19,000 observations. Columns (5) through (8) employ this paper's RRP start date of July 20, 2008 for comparison purposes.[21] In column (1), we attempt to replicate their main result by including controls for location attributes, such as distance to the city center and dummies for whether the housing complex is located within a "key" school district.[22] We attribute the difference in our estimates to having substantially more spatial variation and a more representative data set of the broader Beijing housing market. The addition of detailed controls on the housing attributes reduce the estimates, but the effect is still more than double that of Xu et al. (2015).

Xu et al. (2015) additionally found that the subway distance premium after the road rationing policy ranged between 36-60% of the pre-restriction premium. We estimate the pre-restriction premium for subway accessibility in column (4) and (8) of Appendix Table A2 following Xu et al. (2015) where we limit the sample period to 6 months prior to the policy. Several confounding factors are likely correlated with subway proximity and housing desirability, thus we interpret columns (4) and (8) with caution. For comparison purposes, our results suggest that the post-restriction premium is double the pre-restriction premium, substantially greater than Xu et al. (2015). This underscores that not only was the gradient shift much larger than prior estimates suggest; but the magnitude of this gradient shift is of first order economic significance. This substantial difference in our results implies that subway proximity may be highly correlated with certain disamenities, like noise or congestion, that put downward bias on the housing price-subway distance gradient. Failure to control for these unobserved attributes can significantly underestimate the benefits of transit infrastructure.

5.3 Road Rationing and the Demographic Sorting

The prior section established that price-distance gradients for both business district and subway access became steeper following the road rationing policy. We now explore whether gentrification is a potential mechanisms driving these price effects. This is an empirical question: lower income groups may continue to outbid the rich for locations proximate to the CBD and subway stations if developers supply smaller housing units with a higher price per square meter. If the road rationing policy is more binding for the rich relative to the poor, Eq. 6 and Eq. 7 are less likely to hold and the average income of households proximate to either the CBD and subway stations will increase.

Figures 11 and 12 show estimates of α_q from Eq. 9. Each are generally consistent with the

[21] We believe July 20 is the correct effective start date of the RRP because this was when the policy was implemented for the Olympic games. The policy restricted half of the vehicles from driving on a given work day based on the even or odd license numbers. The policy was modified and made more permanent in October of that year.

[22] Specifically, we replicate column 8 of Table 2 in Xu et al. (2015).

model's prediction: wealthier (poorer) households move closer to (further from) both subway stations and CBD relative to lower (higher) income households after the road rationing policy. Zip code level fixed effects allow us to examine how income changes within a neighborhood over time.

In Figure 11, the outcome variable of interest is distance to the nearest CBD. We show the event study using our main specification of Eq. 9 in the darker shade, as well as a specification with fixed effects for the line of the housing unit's nearest subway station in lighter gray. Accessibility to the CBD will differ across subway lines: lines leading out to airports (the Daxing Airport Express or the Capital Airport Express lines) or radial lines along Beijing's perimeter (e.g., lines 15 or 9) will be less useful for accessing jobs in one of Beijing's CBD relative to the circular lines (e.g., lines 10 and 2) or the east-west lines (eg., lines 1 and 6) that traverse several economically important parts of the Beijing. Comparing specifications on sorting near the CBD with versus without the subway line fixed effects sheds light on the mechanism driving our results.

In both specifications, the difference in CBD proximity across the income distribution is generally stable, and not statistically different from the RRP quarter in periods prior to July of 2008. The two quarters prior to the road rationing policy exhibit some pre-trends, suggesting that higher income individuals were more likely to move to locations closer to CBD relative to lower income groups before the road rationing policy went into effect. The Beijing government enacted a trial period in late 2007 and Beijing news media covered stories on the coming road rationing during the first quarter of 2008. Consequently, it is possible that these pre-trends reflect adjustment to new information on the road rationing policy. Indeed, Google Search trends in Appendix Figure A3 suggest individuals may have anticipated the policy in late 2007 and early 2008.

Figures 11 shows that when employing variation across subway lines (by excluding subway line fixed effects), there is a significant change in the distance to CBD-income gradient. After the road rationing policy, the composition of wealth increases (falls) in areas proximate to (far from) CBD. Comparing two households of different income, the household that is 10% wealthier than another household is likely to live 0.4 to 0.6 percentage points (or about 0.6 to 1 kilometer) closer to the nearest central business district after the road rationing relative to the poorer household. However, after conditioning on variation in the distance-income gradient *within* a subway line, there is no significant difference after the RRP policy relative to before. This suggests that individuals demand locations proximate to the CBD in so far as those locations increase access to CBD. Holding the distance to the nearest subway station fixed, additional subway stops likely have a trivial effect on

total commute times. But commute times may differ substantially across subway lines depending on how linked that line is to jobs. Our results are consistent with this hypothesis.

Table 4 shows the mean change in the income-business district proximity gradient comparing 24 months before versus 24 months after the road rationing policy. The level estimate on household income is negative, suggesting that higher income households are more likely to live proximate to CBD (consistent with Panel A of Figure 7). The gradient becomes steeper after the policy, and is more than double the baseline gradient estimate in some specifications. Results in column (3) show that a household that is 10% wealthier (poorer) is likely to locate 0.5 percentage points closer to (further from) the nearest business district after the RRP compared to before. Conditioning on variation within a particular subway line in columns (4) and (5) reduces the estimate magnitude substantially, and the coefficient is no longer statistically significant. These results are similar after employing alternate definitions of the Beijing CBD, as shown in Appendix Table A3.

We show changes in the distance to subway-income gradient over time in Figure 12. Again, using only variation across households proximate to *the same* subway line to estimate the gradient shift renders different results than allowing for comparisons of households across subway lines. Our results suggest that not all subway stations are valued equally. The gray dots show estimates of α_q in Eq. 9 that exclude subway line fixed effects: there is no noticeable income-based sorting proximate to stations. However, after removing variation across households driven by the connectivity of their nearest subway line to areas of Beijing (darker red dots), there does appear to be a trend break: higher income households differentially sort near subway stations. The gradient shift estimate is small and statistically insignificant in the quarters immediately following the RRP, but becomes marginally significant and larger in magnitude after the second quarter of 2010. In both specifications, there is no significant evidence that higher income households differentially sort near subway stations in periods leading up to the road rationing policy.

Table 5 shows the average difference-in-difference estimate of the RRP effect on the subway distance-income gradient. In columns (4) and (5) where we employ the most restrictive controls, the results show that a household with 10% higher (lower) in income is likely to live 0.8 percentage points closer (further) from the nearest subway station after the RRP relative to before the policy. Given the mean household income and subway proximity in our sample, these estimates imply that a household earning 730 yuan less per month (or about $1,200 per year) will live approximately 0.1 kilometer further from a subway station following the road rationing policy.

While these results on demographic shifts are economically small, they explain approximately 30% of the overall increase from 2006 to 2010 in the elasticity of distance with respect to income.[23] This suggests that city-wide policies aimed at reducing traffic and air pollution can be potentially regressive because they not only increase the premium for center-city locations, but they also increase competition for housing near public transit, the mode choice disproportionately utilized by lower income groups. In absence of Beijing's aggressive subway investments, the housing market and demographic sorting responses would likely be stronger.

The potential regressivity of a city-wide road rationing policy will depend upon the level of enforcement and the potential for behavioral adjustments. For example, if the purchase of new cars in Beijing were unregulated, wealthy car drivers could have circumvented the license-plate based road rationing by purchasing a second car, as in the case of Mexico City (Davis 2008). Such offsetting behavior would likely mitigate the road rationing policy's effect on the housing market and demographic sorting. Beijing's strong compliance rate means that car owners can only adjust through a combination of using public transit and relocating within the city to reduce their total commute time.

5.4 Potential Endogeneity of Subway Locations

Our empirical analysis so far has ignored possible reverse causality in the relationship between housing prices and new subway station locations. The government of Beijing has invested heavily in expanding its subway network over the past two decades. As of 2000, Beijing had two subway lines with 31 stations while today the city has 21 lines with over 370 stations.[24] The placement of these new lines and stations is unlikely to be random. If the location of new subway stations is determined by pre-existing trends in real estate development or gentrification, our results may be spurious.

We address these concerns in several ways. First, we test whether subway stations are more likely to open in gentrifying neighborhoods relative to stagnant, or declining neighborhoods. In Appendix Figure A8, we find the population weighted mean of household income by jiedao in each quarter-of-year and compare changes in mean income across quarters leading up to and following the opening of a subway station in that jiedao. There is no evidence of a significant upward trend in household income preceding the opening date of a station, suggesting that across Beijing, siting of

[23] As of 2006, the elasticity of distance to the CBD (subway) with respect to income was approximately -0.62 (-0.77). As of 2010, the elasticity of distance to the distance to the CBD (subway) with respect to income was approximately -0.77 (-1.05). We calculate these using cross sectional regressions of ln(distance) as a function of ln(household income) with year-by-month fixed effects.

[24] Appendix Figure A1 shows how the subway network has expanded substantially over the last two decades, particularly since 2010.

new stations is not directly correlated with income growth, consistent with Li et al. (2016).

We next exclude housing units in areas of the city that received a new subway station. For this sensitivity check, our sample includes only housing units that maintained the same distance to their nearest subway station from 2005 through 2016. Approximately 1,200 building complexes in our sample met this criteria, leaving about 50% of all transaction observations. Relying purely on time-series variation, rather than spatial variation in subway expansion, results of the bid-rent gradient shift for subway proximity are consistent with our main results. The bid-rent gradient in Appendix Figure A9 demonstrates a substantial tilt following the road rationing policy. Appendix Table A4 shows estimates of the price-distance to subway gradient for this restricted sample. The gradient change is attenuated but within a standard deviation of our main results in Table 3. For housing units with no change in their proximity to the nearest subway station, the road rationing policy increased the premium for these units by an additional 1.2% per kilometer compared to 3.5% estimated from our full sample in Table 3 (based on column (4) of both tables). We interpret these results as a lower bound on the increased demand for subway proximity. The subway stations near this housing subsample are some of the oldest lines and stations in the system network (Beijing's oldest lines were built in 1969 and 1971, without substantial additions until the mid-2000's) thus proximity to these areas may be less desirable to the extent that these lines offer less network advantages and may run less efficiently compared to the newer lines.

Lastly, we test whether areas that received *future* subway development after our study period experienced differential price trends over time. In Appendix Figure A10, we estimate the effect of subway proximity among a sample of housing units that were outside of walking distance from a subway station up through 2013, but came to be within walking distance after new stations were built after 2013. This sample of housing units should not be affected by the road rationing policy during our study period because they were not within walking distance of subway stations until five years after the policy. Any price effects from the policy would raise concern that correlated shocks stemming from unobserved economic investment or growth caused the price-distance to subway gradient shift, as opposed to increased demand for the subway itself. We define "walking distance" as three kilometers of a station, based on our non-parametric estimates in Figure 10. Appendix Figure A10 is suggestive that the road rationing policy did not significantly increase the price premium for subway proximity among this group of housing units. The point estimates are imprecisely estimated due to smaller sample sizes in the post-RRP period. However, the quarterly estimates do not show a clear upward

trend, as in Figure 9.

5.5 Additional Robustness Checks

We carry out additional robustness checks to verify our results. To begin, demand for subway station proximity may have increased over time as a result of the improved subway network in a way that is not fully captured by existing controls in our baseline specification. To explore this possibility, we add controls for a housing unit's subway network density as well as an interaction of density with distance to station to our baseline specifications. We construct a measure of a location-specific network density over time. We divide our study area within the Fifth Ring Road into 516 transit zones following the sampling unit used by the Beijing Transportation Institute for their commuting surveys. For each zone, we measure it's subway density as the inverse distance-weighted sum of stations from the zone's centroid. The zone-specific density measure increases over time as the subway system expands. Zones closer to stations have a higher network density measure than zones further from stations. Appendix Table A5 shows that the additional subway network density control does not change our baseline results. Further, network density and its interaction with kilometers to subway appear to provide no additional information on the variation between distance and price. The coefficient estimates are near zero with small standard errors.

We conduct a final placebo analysis to test whether the RRP adjusted either prices or the spatial distribution of wealth in areas close to *undesirable* locations of the city. This test informs whether we are justified in interpreting our main results as a consequence of people's desire to reduce commuting costs. A restriction on traveling by car during the week should not affect the (un)desirability of proximity to major pollution sites.

We obtained data on major sources of pollution throughout Beijing as of 2006 and 2007 from the emissions monitoring program of the Ministry of the Environmental Protection. These data provide the location and emissions level of industrial pollution sources. We isolated firms in the top 10th percentile of total air discharge, and geocoded their locations. We then estimate the same hedonic and sorting specifications based on Eqs. 9 and 8, respectively. Some major pollution sources are also major employment locations. Unfortunately, we are unable to observe employment associated with the pollution sources. To ensure that we do not conflate commuting effects with the dis-amenity effects of pollution sites, we restrict our sample of pollution sites to those that are at least 3 kilometers away from a major central business district. This leaves a sample of 114 pollution sites throughout Beijing, out of a total of 449 sites. Appendix Figure A11 compares our main estimates on the price-distance

gradient shifts for subway and CBD proximity shown in black to that of proximity to major pollution locations shown in gray. "M1" through "M6" denote various specifications of the hedonic regression. The placebo estimates are generally smaller in magnitude than our main hedonic estimates, and are statistically indistinguishable from zero. Appendix Figure A12 shows results of a similar exercise for income-sorting. Again, the placebo estimates (shown in gray) of the effect of the RRP on the elasticity of distance with respect to household income are statistically indistinguishable from zero. These findings demonstrate that price-distance gradients and income sorting did not change in all parts of the city after the RRP. Rather, the RRP increased desirability of areas that are most accessible to major employment centers of the city.[25]

5.6 Sorting Mechanisms

While the prior analysis documented how the RRP increased the price and mean household income of housing units close to economically important areas of Beijing, it is not clear whether these sorting effects are a result of displacement of poorer households, or gentrification and development of new housing. Evidence of displacement raises equity concerns for the incumbent households. We explore which mechanism explains the sorting results by testing first, whether total housing stock increased and second, whether the number of lower income households fell in absolute terms in areas proximate to subways and the CBDs over time.

We delineate "proximity" at 5 kilometers because this is the mean distance to the nearest CBD in our sample and because demand for subway proximity attenuates at this distance. By neighborhood, we count the number of newly built housing by month in locations within versus over 5 kilometers of subways and CBD. We then take the mean of new builds across neighborhoods, and plot these values by month in Figure 13. Panel A shows that new development increased after the RRP in areas within 5 kilometers of subway stations more so than areas over 5 kilometers from subway stations. Panel B shows that new development exhibited a similar upward trend in areas both close and far from Beijing's CBD. These figures suggest that housing supply adjusted to the increased demand for housing near city centers. This may explain why the price effects for proximity (show in Figure 8 and 9) reverted to pre-RRP levels in the three years following the RRP.

We repeat this non-parametric approach in Panels C and D with a focus on count of high relative to low income households. We first look only at households living within 5 kilometers of either subway

[25] Using similar housing transactions data and the geocoded major polluters in Beijing, Barwick et al. (2019) show that the price-distance gradient with respect to the nearest major polluter became steeper after the national pollution monitoring and information disclosure program that rolled out in three waves across cities starting from 2013.

stations or CBD. We then divide this sub-sample into households above median versus below median income, where the median is calculated using the pre-RRP distribution from January 2005 through July 2008. We count the number of households in each income category by neighborhood, and plot the count changes over time. Panels C and D show a clear upward trend in the number of higher income households in proximate locations, whereas the count of lower income households stays relatively flat. Based on the data patterns in these figures, it does not appear that lower income households were displaced from proximate locations. Instead, these patterns are suggestive that newly-built housing in desirable areas of Beijing are occupied by higher income households.

6 Conclusion

Road rationing policies are an increasingly common policy instrument used among major cities to reduce traffic congestion and air pollution. While prior work has investigated the effectiveness of these policies at improving air quality and congestion, less is known about the ramifications of these policies on the residential location decisions and urban spatial structure. Urban land use theory provides predictions on how such policies could impact the housing market and the sorting of demographic groups relative to one another. Although the monocentric city model remains a dominant tool to explain urban spatial structure, quasi-experimental tests of its predictions on bid-rent gradients are somewhat mixed. Quasi-experimental tests of its predictions of income sorting are fewer still.

This paper uses detailed, micro-level data on home purchases and buyer demographics in combination with a city-wide road rationing to empirically test these theories in the context of Beijing, China. Our analysis relies on fine-scale spatial fixed effects to control for location-specific correlates of public transit. We find that the road rationing policy required prospective home-buyers to pay an additional $3,000 on average for a one-kilometer reduction in distance to a subway station. The premium for central business district proximity also increased, but by a smaller magnitude of approximately $1,000 per kilometer. Considering that the average Beijing household earns approximately $12,000 (86,000 yuan) per year, these effect sizes are economically large. We additionally utilize novel micro data on household income and housing locations to explore how the road rationing policy impacted the residential location choices of different income groups. Following the policy-induced shocks to housing prices, the composition of households living close to subway stations as well as close to Beijing's CBDs shifted toward wealthier households.

These results underscore the relevance of the transit-based explanation championed by LeRoy and Sonstelie (1983) to explain patterns of income sorting in cities. Further, by focusing on a scenario

where urban commuting costs *increase*, our study provides rare insight into the universality of the monocentric city model. Where prior literature has shown that declining transportation costs have flattened bid-rent gradients over time (McMillen 1996; Ahlfeldt and Wendland 2011), our study shows the reverse holds and price-distance gradients become *steeper* when transportation costs increase.

From a policy perspective, our study provides evidence that city-wide road rationing policies can have the unintended consequence of limiting access to public transit for lower income individuals. Such effects are likely to be stronger in markets where car ownership is cost-prohibitive to the poor and when enforcement of road rationing is strict. Our findings expose several important avenues for future research: first, the welfare implications of road rationing policies are not clear and will depend upon how commute times and exposure to pollution change among the wealthy relative to the poor. Such analysis can inform whether rent stabilization or a welfare transfer process may be necessary to offset impacts of road rationing policies on housing affordability. Second, how might a market-based instrument such as congestion pricing affect household location decisions and urban spatial structure relative to a road rationing policy? Understanding the welfare impacts and the distributional consequences of market-based versus command-and-control approaches warrants future research.

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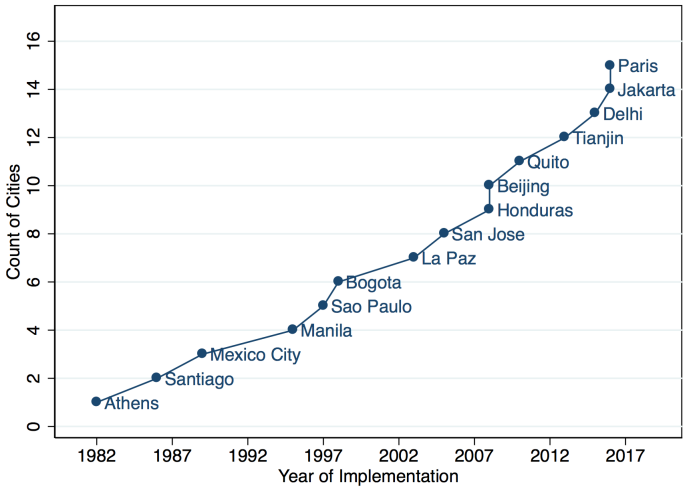
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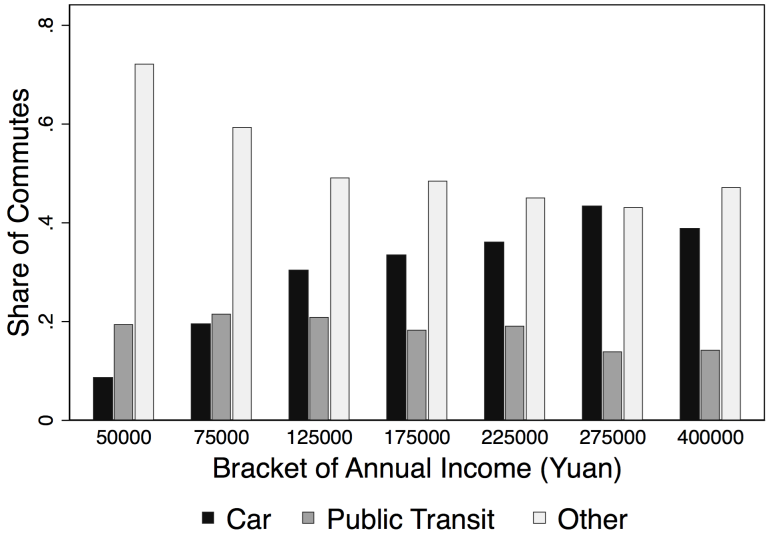
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Figure 1: Global Growth in Urban Road Rationing Policies



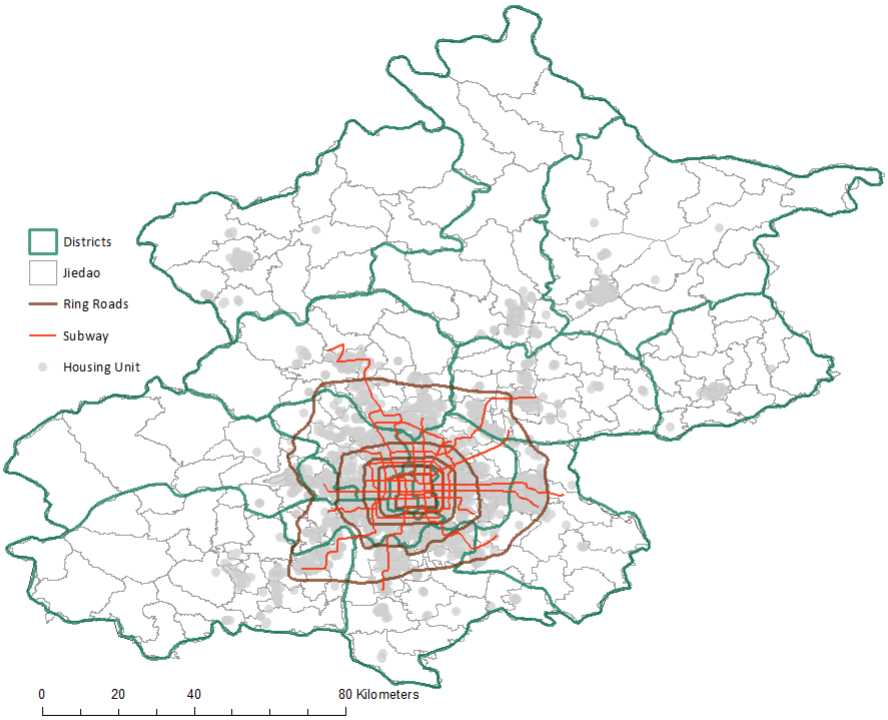
Sources: ChinaDaily.com (http://www.chinadaily.com.cn/china/2013-12/16/content_17175846.htm); BBC.com (https://www.bbc.com/news/world-europe-38236926); and Wikipedia article on "Roat Space Rationing" (https://en.wikipedia.org/wiki/Road_space_rationing)

Figure 2: Transit Mode Choice by Income



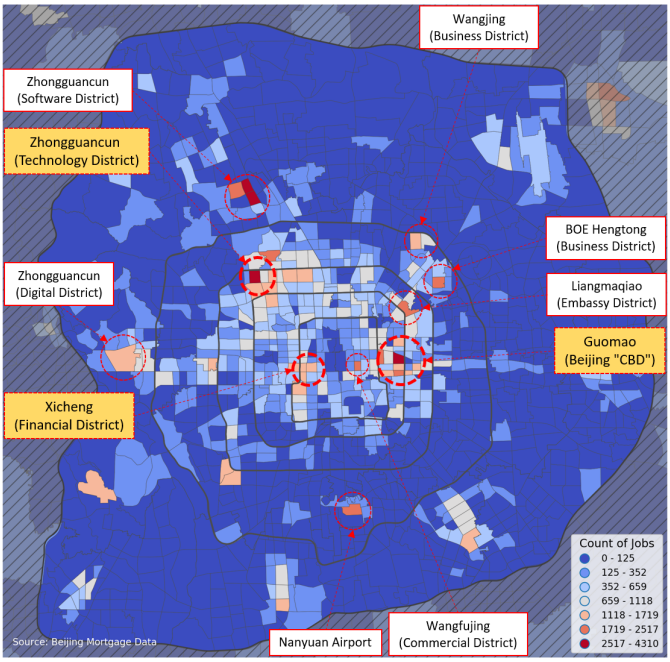
Note: Data sourced from 2010 Beijing Household Travel Survey (Beijing Transport Institute 2010). Based on 276,377 responses. "Other" includes walking, cycling, taxi, company shuttle, mixed modes.

Figure 3: Housing Units & Subway Stations in Beijing



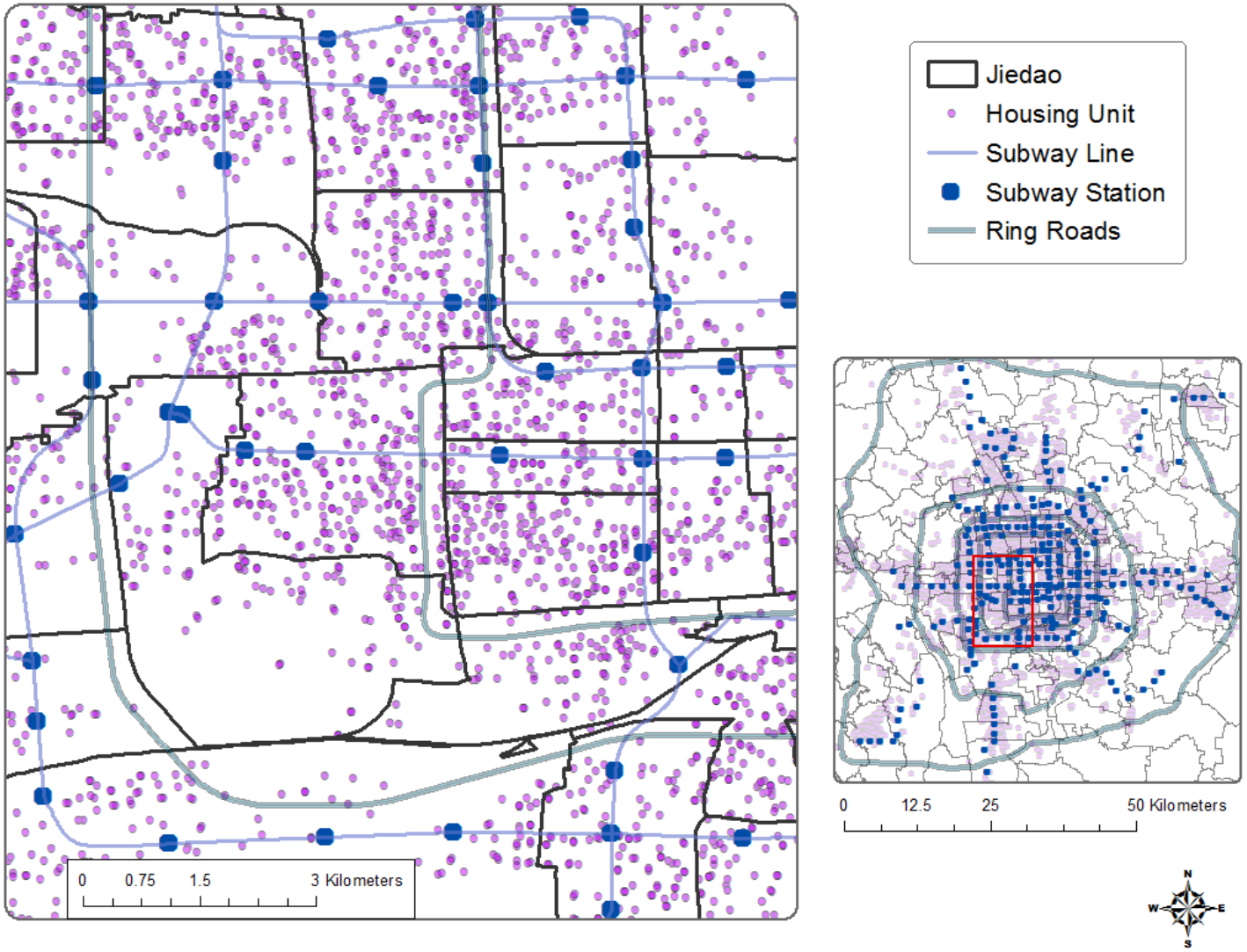
Note: Figure shows the location of housing units purchased between 2005-2014 throughout Beijing. Source: Beijing Real estate data.

Figure 4: Business Districts of Beijing



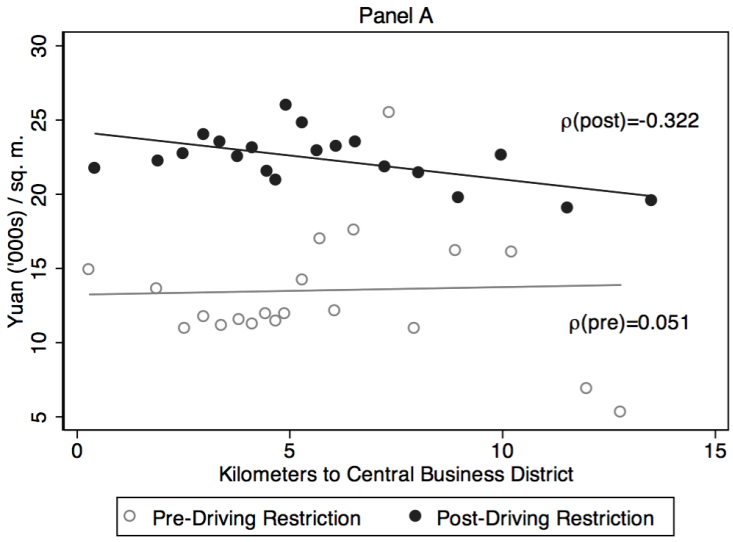
Note: Figure shows employment concentration by transportation analysis zone (TAZ), the sampling unit used by the Beijing Transportation Institute for their commuting surveys. "Count of Jobs" measures the frequency from 2005-2014 with which home buyers reported the location of their employer in that TAZ. Employer locations sourced from the mortgage application data. See Section 2 for details.

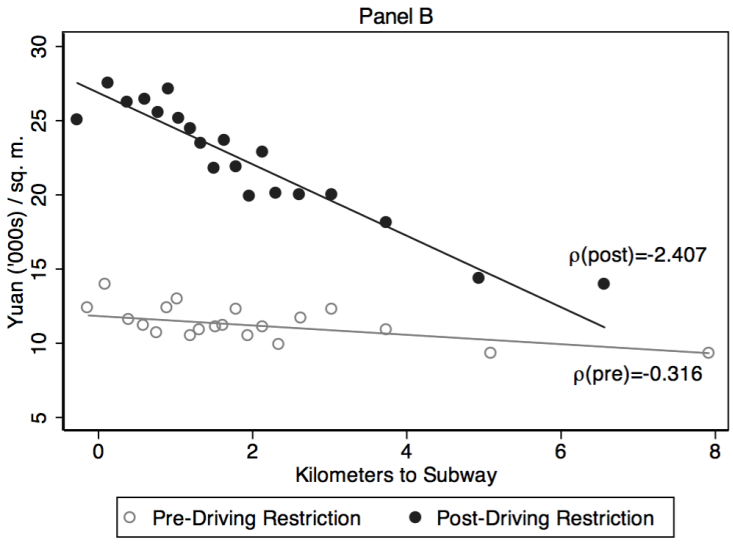
Figure 5: Neighborhood Variation



Sources: Beijing Real estate data; mortgage application data. Figure shows a southwest section of central Beijing, between the second and third ring roads. Roard Rationing Policy effects are identified based off of variation in distance to subway stations, or distance to the nearest CBD across housing units *within* a jiedao.

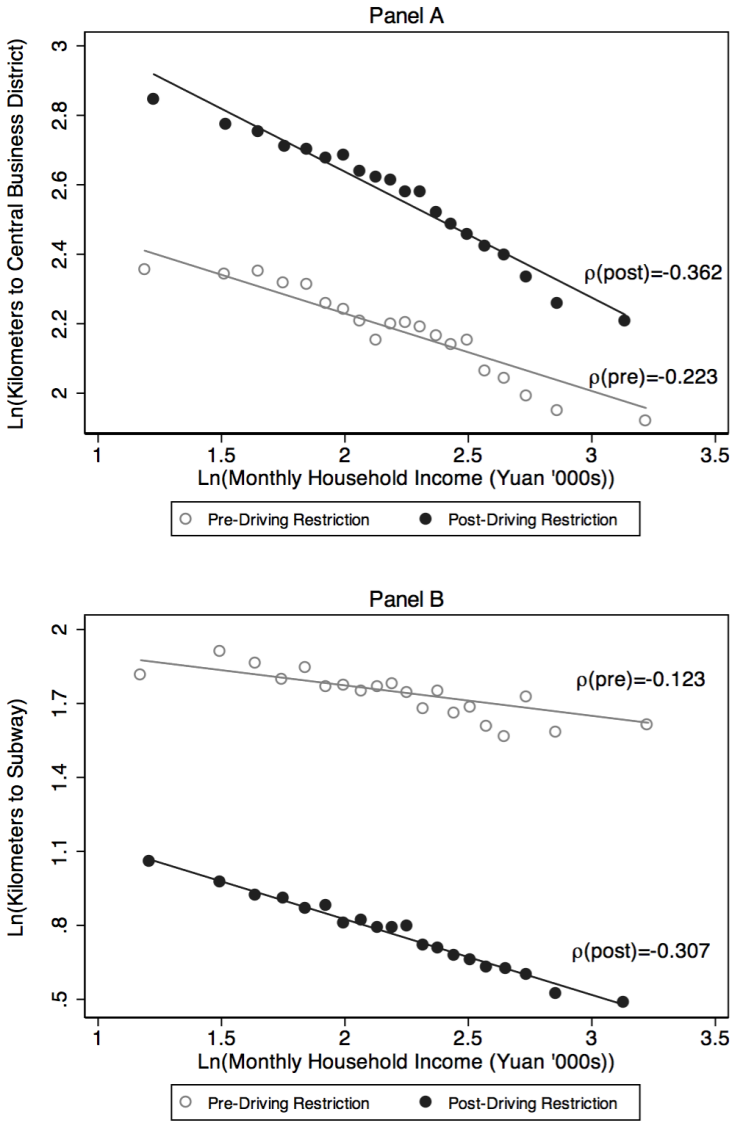
Figure 6: The Price-Distance Gradient and Beijing's Road Rationing Policy





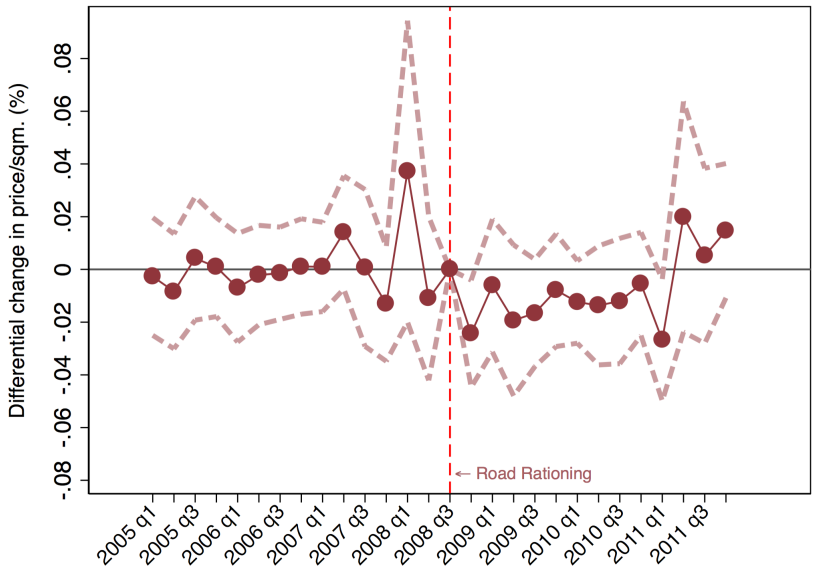
Note: Figures plot the mean house price for each of 20 distance bins. Each dot represents 6,200 and 12,870 observations per bin in pre- and post-road rationing periods, respectively. Panel A means are residualized by distance to the nearest subway. Panel B means are residualized by distance to the central business district. "Central Business District" defined as the closest of 7 main business districts. ρ(pre) and ρ(post) are regression coefficients. Includes years 2005-2014. Source: Real estate transaction dataset.

Figure 7: The Distance-Income Gradient and Beijing's Road Rationing Policy



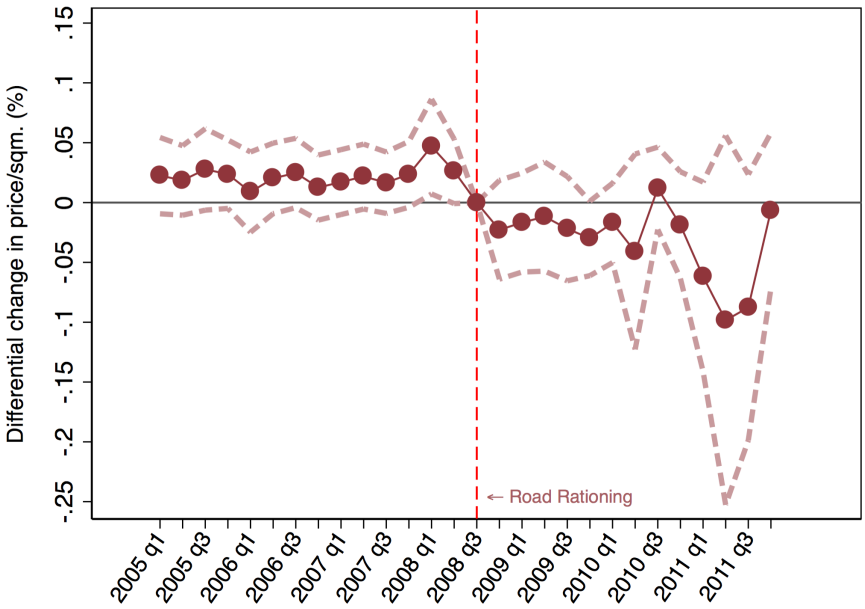
Note: Figure plots mean distance for each of 20 income bins. Each dot represents 840 and 3670 observations per bin in pre- and post-road rationing periods, respectively. Panel A means are residualized by ln(distance to the nearest subway). Panel B means are residualized by ln(distance to central business district). "Central Business District" defined as the closest of 7 main business districts. ρ(pre) and ρ(post) are regression coefficients. Includes years 2005-2014. Source: Mortgage application dataset.

Figure 8: The Effect of the Road Rationing on the House Price-Distance to CBD Gradient



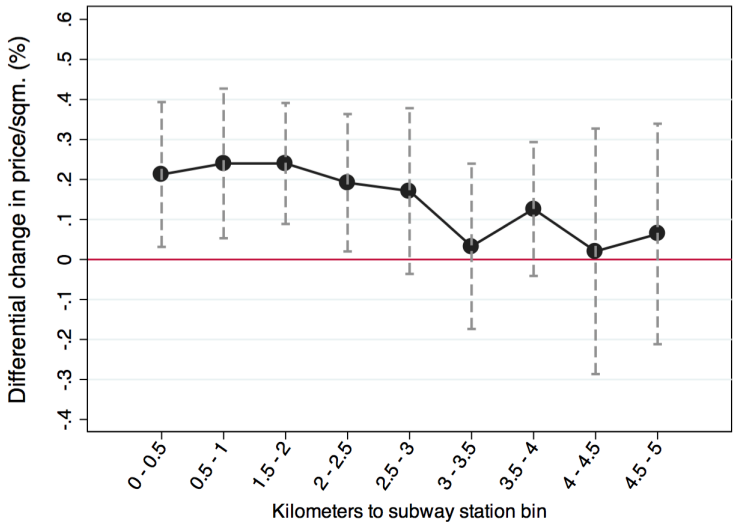
Note: Figure shows the partial effect of distance to central business district on housing price ln(total price/sqm in ¥2007) at each quarter between Jan 2005 and Dec 2011. The omitted quarter is July-October 2008. Dashed lines show 95% confidence intervals. Sample includes 322,686 transactions. Controls include fixed effeects for unit type (resale or newsale), jiedao, and year-quarter; as well as controls for distance to subway, age, age^2, size, floor-area ratio, green space, property management fee, parking fee, number of housing units and building units in complex, and unit size. Standard errors clustered at jiedao level. "CBD" (Central Business District) defined as the closest of 7 main business districts. Sample restricted to units located within 10km of their closest CBD.

Figure 9: The Effect of the Road Rationing on the House Price-Distance to Subway Gradient



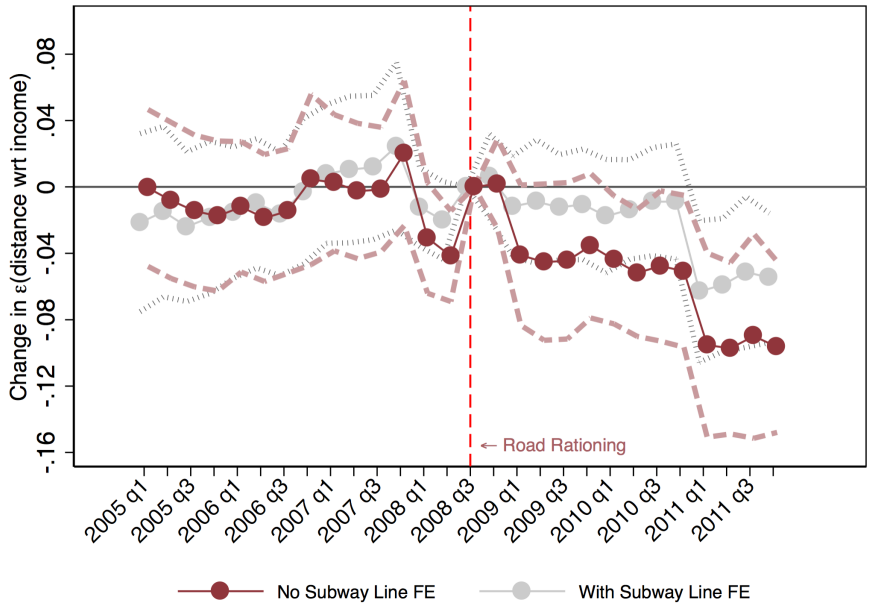
Note: Figure shows the partial effect of subway distance on housing price ln(total price/sqm in ¥2007) at each quarter between Jan 2005 and Dec 2011. The omitted quarter is July-October 2008. Dashed lines show 95% confidence intervals. Sample includes 256,149 transactions. Controls include fixed effects for unit type (resale or newsale), jiedao and year-quarter; as well as controls for distance to nearest CBD, age, age^2, size, floor-area ratio, green space, property management fee, parking fee, number of housing units and building units in complex, and unit size. Standard errors clustered at jiedao level.

Figure 10: Average Effect of Road Rationing on Housing Prices by Subway Distance Bin



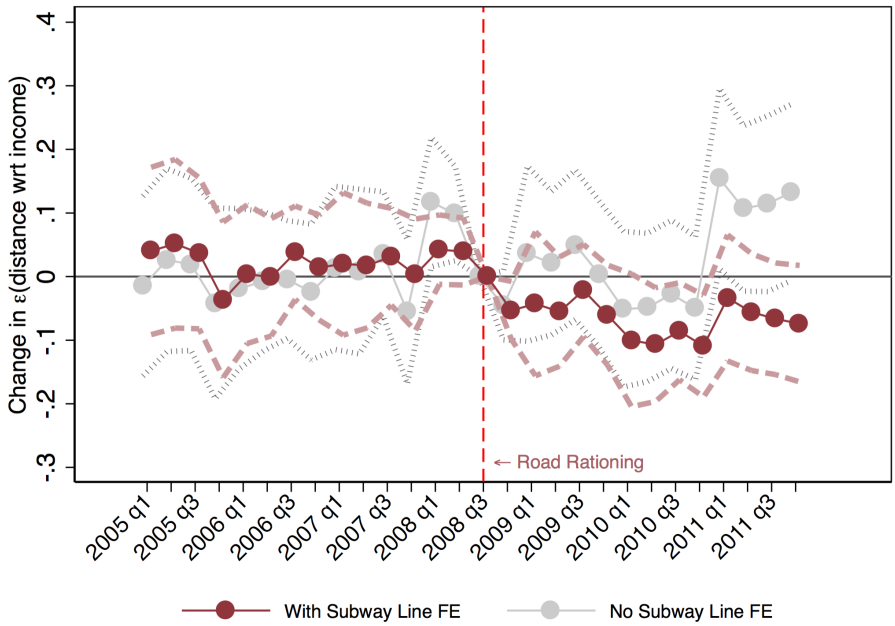
Note: Figure plots α_b, estimates of the average change in housing price per square meter (y) following the road rationing policy (RRP) by half-mile distance bins to subway stations (I_b): $y_{ijt} = \sum_b \alpha_b(I_b \times RRP_t) + \sum_b \kappa_b(I_b) + \rho RRP_t + \mathbf{X}_{ijt}\theta + \gamma_j + \tau_t + \varepsilon_{ijt}$. The reference bin includes housing units over 5 kilometers from subway stations. Dashed lines represent 95% confidence intervals. Includes transactions from July 2006 through July 2010. Controls ($\mathbf{X}$) include fixed effects for unit type (resale or newsale), jiedao (γ_j), year, month of transaction (τ), total number of floors in building, decoration level, whether at top floor, and facing direction; as well as controls for age, age^2, size, floor-area ratio, green space, number of housing units and building units in complex, and unit size. Standard errors clustered at jiedao level.

Figure 11: The Effect of Road Rationing on the Distance to CBD-Income Gradient



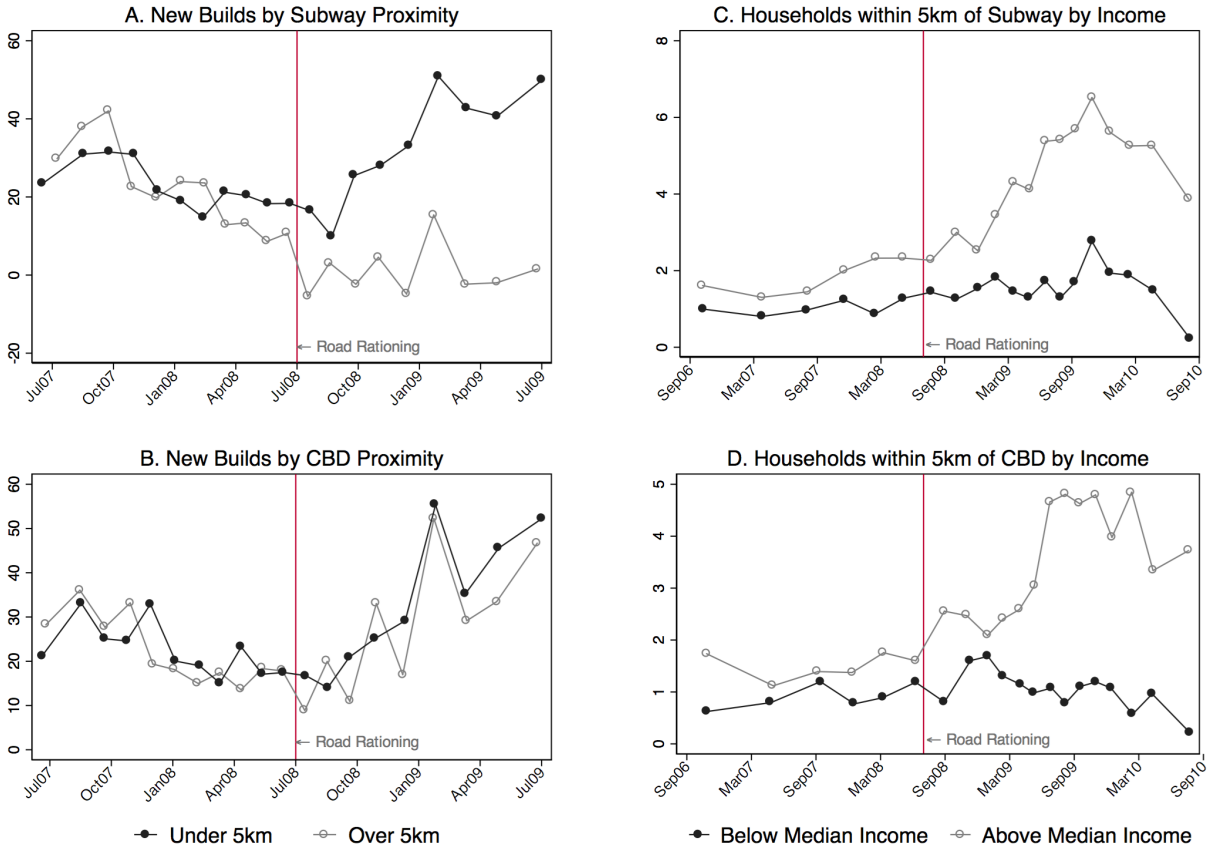
Note: Figure shows the partial effect of income on distance to CBD at each quarter between January 2005 and December 2011. The omitted quarter is July-October 2008. Dashed lines show 95% confidence intervals. Controls include fixed effects for year, month, neighborhood, age, rank, education, and experience of buyers, and a control for distance to nearest subway station. Estimates in gray denote a specification that includes fixed effects for the subway line associated with the housing unit's nearest subway station. Standard errors clustered by zip code.

Figure 12: The Effect of Road Rationing on the Distance to Subway-Income Gradient



Note: Figure shows the partial effect of income on distance to the nearest subway station at each quarter between January 2005 and December 2011. The omitted quarter is July-October 2008. Dashed lines show 95% confidence intervals. Includes FE for year, month, neighborhood, age, rank, education, and experience of buyers, the subway line associated with the housing unit's nearest subway station, and a control for distance to nearest CBD. Gray denotes a specification that *excludes* the subway line fixed effects. Standard errors clustered by zip code.

Figure 13: Supply of New Housing and Road Rationing



Note: Panels (A) and (B) plot the mean new supply of housing by month for units under versus over 5km of subway stations and the CBD, respectively. Sourced from the real estate transaction dataset. Panles (C) and (D) plot mean number of households living within 5km of both Subway stations and the nearest central business district by income group. Median income is based on the pre-road rationing income distribution and is calculated from all mortgage applications occuring from January 2005 through July 2008. Sourced from the mortgage application dataset. Means in all panels residualized by neighborhood fixed effects.

Table 1: Estimation Sample Descriptive Statistics

	Real Estate Transactions		Mortgage Data	
	Mean	(St. Dev)	Mean	(St. Dev)
Total purchase price ('07 Yuan)	1,491,405.7	(1,090,428.9)	599,805.8	(303,918.9)
Price per sq.m	13,274.5	(4,763.8)	6,225.8	(2,805.9)
Unitsize (sq.m.)	107.8	(48.7)	100.6	(33.3)
Km to subway	3.3	(2.7)	15.2	(14.7)
Km to nearest CBD	6.1	(3.9)	20.5	(14.6)
Km to City Center	9.2	(3.7)	26.9	(17.1)
Building Age	10.7	(7.1)	6.4	(7.4)
Building Floor-to-Area Ratio	2.9	(1.3)	2.2	(1.0)
Building Green space ratio	0.3	(0.1)	33.1	(7.4)
Household Monthly Income ('07 Yuan)			7,723	(4,502)
Age of household head			35.2	(6.6)
Years of work experience of household head			13.4	(7.8)
Education level of household head (mode)			Bachlor's	
No. Complexes	4,403		3,971	
No. Neighborhoods	188		183	
Total Observations	252,426		46,471	
Observations by year:				
2005	1,926		4,858	
2006	61,348		5,273	
2007	47,837		4,410	
2008	24,759		4,225	
2009	65,513		12,513	
2010	34,859		8,321	
2011	16,184		6,871	

Note: The unit of observation for the Real Estate Transaction data is a housing purchase transaction. The means calculated in column (1) are calculated using pre-road rationing policy months July 2007 through July 2008. The unit of observation for the Mortgage Data is a mortgage loan application, or a household, equivalently. The means in column (3) are calculated using pre-road rationing policy months July 2006 through July 2008.

Table 2: The Effect of Road Rationing on the House Price-Distance to CBD Gradient: Mean Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Km to CBD x CDR	-0.005	-0.014**	-0.013***	-0.013***	-0.019**	-0.002
	(0.010)	(0.007)	(0.005)	(0.005)	(0.007)	(0.004)
Km to CBD	-0.035***	-0.005	0.012	0.010	0.015	
	(0.009)	(0.017)	(0.017)	(0.016)	(0.016)	
Jiedao FE		Y	Y	Y	Y	Y
Controls			Y	Y	Y	Y
Year-Month FE				Y		
DistrictxYear-Month Trend					Y	
Building Complex FE						Y
Avg Proximity Premium / Km	$425.59	$1187.01	$1141.44	$1079.57	$1601.99	$176.53
Observations	82002	82002	82002	82002	82002	81547
Adjusted R^2	0.184	0.513	0.609	0.619	0.614	0.827

Note: Dependent variable is ln(total price per square meter in 2007 real Yuan). Standard errors clustered at jiedao level. Sample spans 12 mos. before and after CDR. All specifications include year and month fixed effects. Average price premium is evaluated at a unit size of 122 sqm, the size at the mean distance to the nearest business district (5 and 7 km), and at a conversion rate of 6.95 yuan per USD. Controls include fixed effects for unit type (newsale vs resale), top floor, floor level, facing direction, no. bedrooms, decoration level, ownership type, and total number of floors in building. Continuous controls include distance to nearest subway station, age, age2, size, floor-area ratio, green space, property management fees, parking fees, and size, number of housing units and number of buildings of the complex. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: The Effect of Road Rationing on the House Price-Distance to Subway Gradient: Mean Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Km to Subway x CDR	-0.046**	-0.044***	-0.040***	-0.035***	-0.038***	-0.026**
	(0.020)	(0.012)	(0.011)	(0.011)	(0.010)	(0.012)
Km to Subway	-0.048***	-0.003	-0.018**	-0.017**	-0.018*	-0.014*
	(0.014)	(0.013)	(0.009)	(0.008)	(0.010)	(0.008)
Jiedao FE		Y	Y	Y	Y	Y
Controls			Y	Y	Y	Y
Year-Month FE				Y		
DistrictxYear-Month Trend					Y	
Building Complex FE						Y
Avg Proximity Premium / Km	$3772.96	$3556.21	$3256.27	$2877.02	$3079.41	$2127.93
Observations	82002	82002	82002	82002	82002	81547
Adjusted R^2	0.161	0.517	0.612	0.621	0.615	0.829

Note: Dependent variable is ln(total price per square meter in 2007 real Yuan). Standard errors clustered at jiedao level. Sample spans 12 mos. before and after CDR. All specifications include year and month fixed effects. Average price premium is evaluated at a unit size of 115 sqm, the size at the mean distance (between 2 and 4 km) to the nearest subway station, and at a conversion rate of 6.95 yuan per USD. Controls include fixed effects for unit type (newsale vs resale), top floor, floor level, facing direction, no. bedrooms, decoration level, ownership type, and total number of floors in building. Continuous controls include distance to nearest CBD, age, age2, size, floor-area ratio, green space, property management fees, parking fees, and size, number of housing units and number of buildings of the complex. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: The Effect of Road Rationing on the Distance to CBD-Income Gradient: Mean Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(Household Income)× CDR	-0.034	-0.052***	-0.051***	-0.048***	-0.038**	-0.016	-0.012
	(0.081)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)
Ln(Household Income)	-0.756***	0.007	0.009	0.008	0.004	-0.009	-0.008
	(0.106)	(0.014)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
Zip FE		Y	Y	Y	Y	Y	Y
Controls			Y	Y	Y	Y	Y
Year-Month FE				Y		Y	
Subway Line FE						Y	Y
DistrictxYear-Month Trend					Y		Y
Observations	18135	18135	18135	18135	18135	18135	18135
Adjusted R^2	0.201	0.944	0.944	0.945	0.947	0.956	0.958

Note: Dependent variable is ln(Distance to CBD (km)). Income is household monthly income ('000 yuan). CDR equals 1 after July 20 2008. Standard errors clustered by zip code. Sample spans July 20, 2006-July 20, 2010. All specifications include controls for year, month, and distance to subway. Controls include husband and wife age, employment rank, education, employer type, and tenure. Subway Line FE is a fixed effect for the subway line associated with the housing unit's closest subway station. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

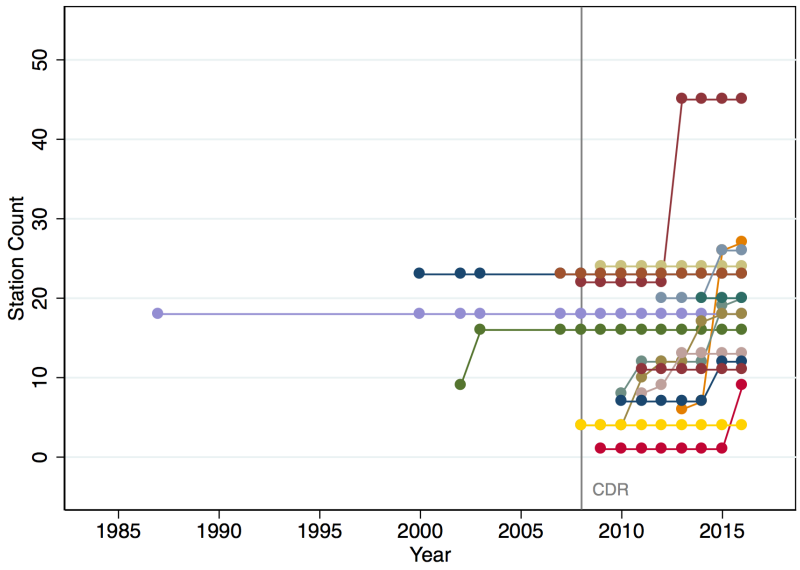
Table 5: The Effect of Road Rationing on the Distance to Subway-Income Gradient: Mean Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(Household Income)× CDR	-0.043	-0.014	-0.016	-0.025	-0.014	-0.083***	-0.079***
	(0.077)	(0.050)	(0.049)	(0.048)	(0.049)	(0.024)	(0.026)
Ln(Household Income)	-0.141*	0.003	0.006	0.012	0.007	0.050**	0.048**
	(0.073)	(0.037)	(0.035)	(0.035)	(0.034)	(0.022)	(0.022)
Zip FE		Y	Y	Y	Y	Y	Y
Controls			Y	Y	Y	Y	Y
Year-Month FE				Y		Y	
Subway Line FE						Y	Y
DistrictxYear-Month Trend					Y		Y
Observations	18135	18135	18135	18135	18135	18135	18135
Adjusted R^2	0.637	0.912	0.913	0.913	0.915	0.923	0.924

Note: Dependent variable is ln(Distance to Subway (km)). Income is household monthly income ('000 yuan). CDR equals 1 after July 20 2008. Standard errors clustered by zip code. Sample spans July 20, 2006-July 20, 2010. All specifications include controls for year, month, and distance to nearest CBD. Controls include husband and wife age, employment rank, education, employer type, and tenure. Subway Line FE is a fixed effect for the subway line associated with the housing unit's closest subway station. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

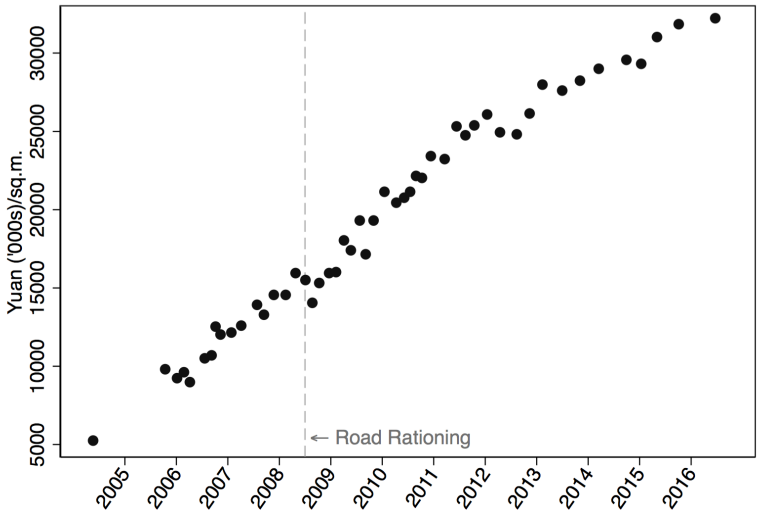
Appendix A Figures and Tables

Figure A1: Beijing Subway System Expansion



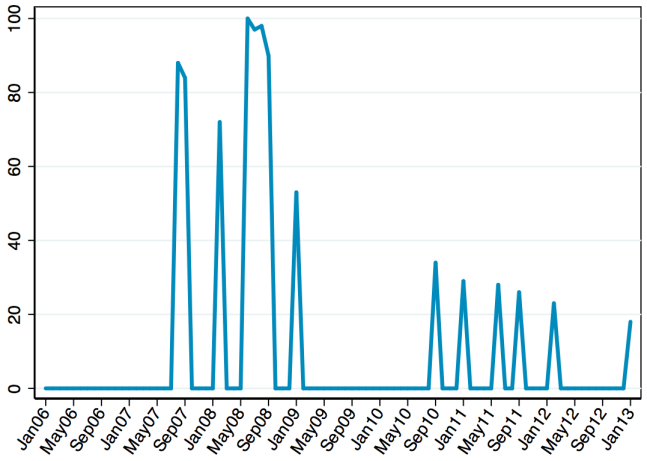
Note: Each color represents a subway line. Each dot denotes a date on which atleast one subway station was added across the Beijing system. Vertical shifts within a subway line show additions of stations connected to that subway line.

Figure A2: Beijing Housing Price Appreciation, 2005-2016



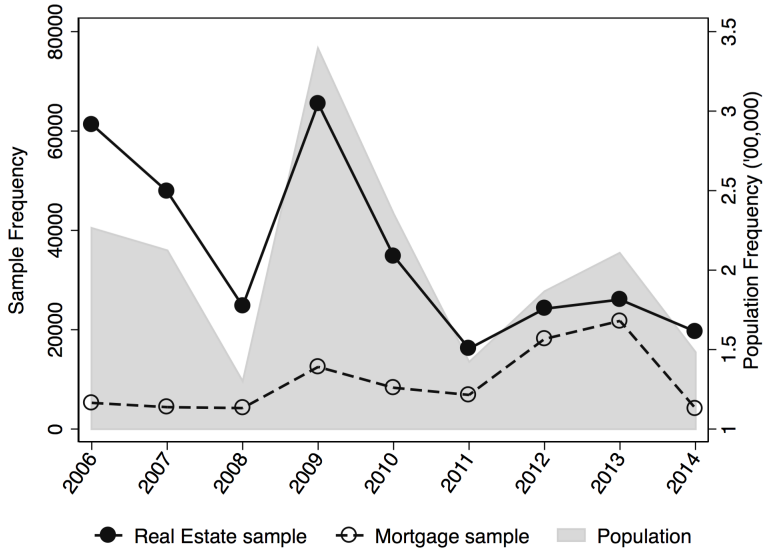
Note: Figure plots mean house price per square meter for 50 bins for transactions occuring from 2005 through 2016. Means residualized by jiedao fixed effects. Thus figure shows mean price appreciation within a jiedao over time. Source: Real estate transaction dataset.

Figure A3: Google Search Trend Index for "Beijing Odd Even"



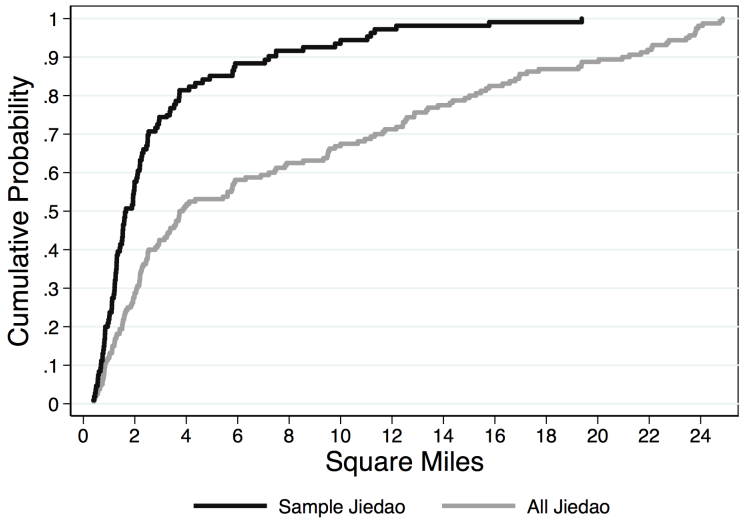
Note: Figure plots the relative popularity in Google searches worldwide for the term "Beijing Odd Even". Each data point is scaled on a range of 0 to 100 based on a topic's proprotion to all searches on all topics.

Figure A4: Comparison of Sample vs Population of Housing Transaction Volume



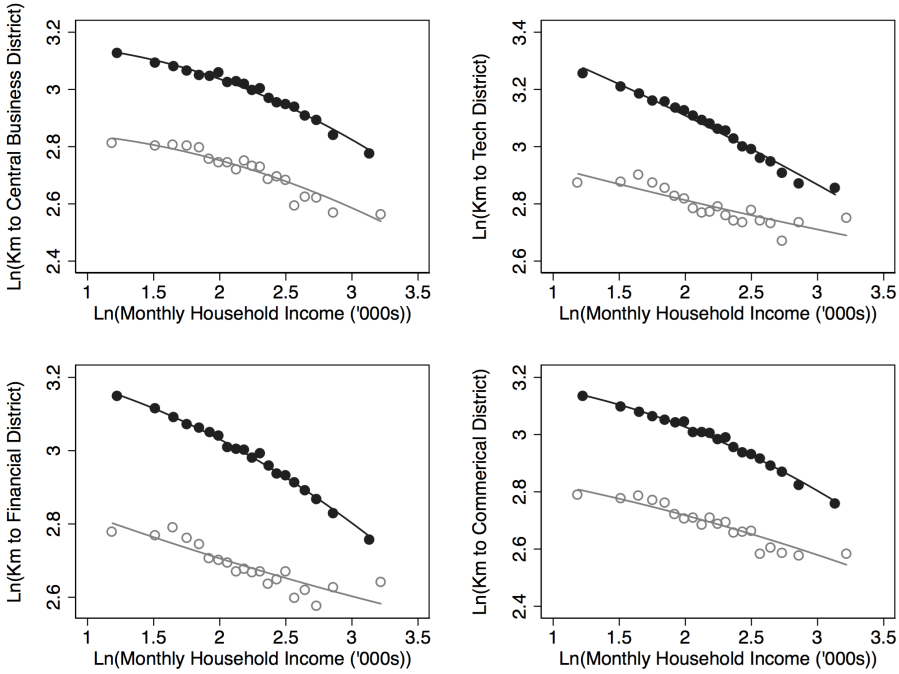
Note: Figure plots the population of housing transactions in Beijing from 2006 through 2014 in solid gray. Annual transaction volumes associated with the Real Estate data and Mortgage Applicaiton data shown in the solid and dashed black lines, respectively.

Figure A5: Distribution of Jiedao Size



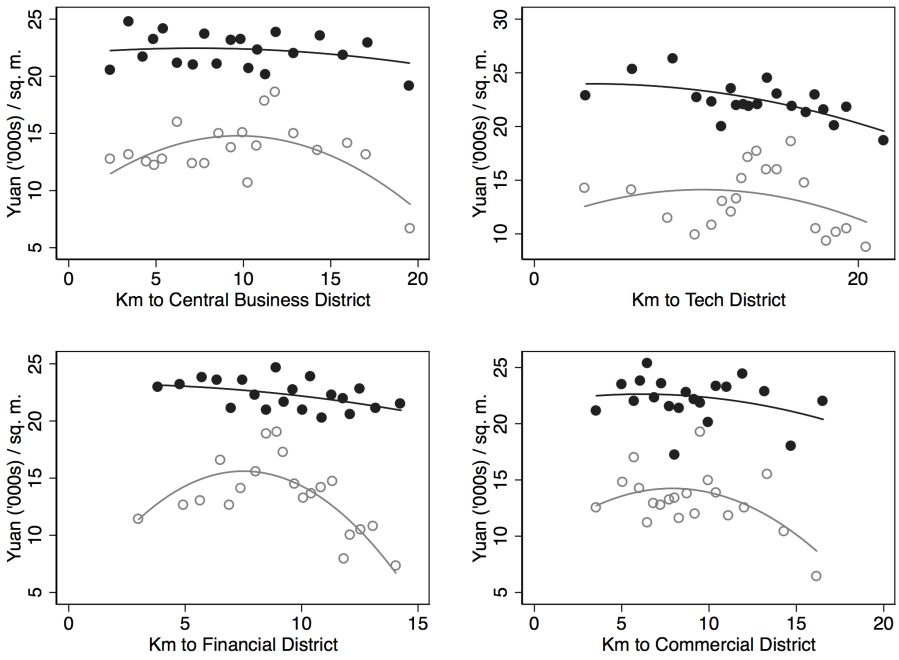
Note: Sample Jiedao include 188 neighborhoods. "All Jiedao" include population of neighborhoods, or 307 jiedao.

Figure A6: Distance-Income Gradient with various definitions of "CBD"



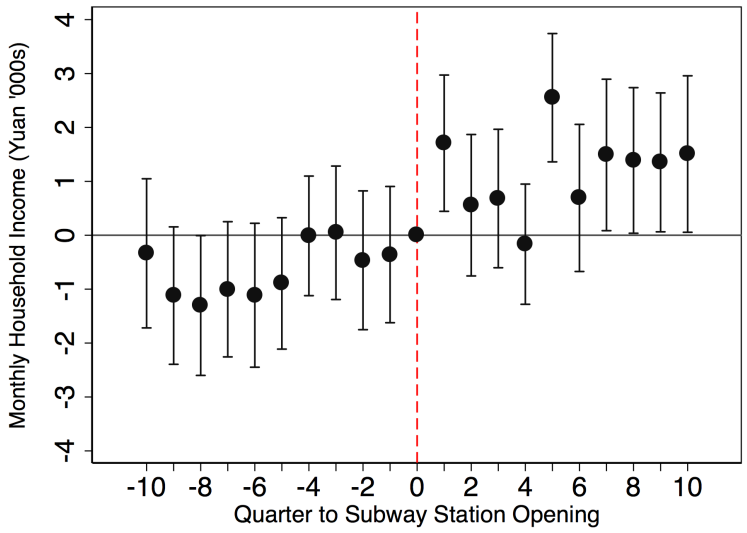
Note: Figure plots mean distance to CBD by household income bin. Includes 20 bins each with 840 and 3670 observations per bin in pre- and post- road rationing periods, respectively. Means residualized by ln(distance to the nearest subway).

Figure A7: Price-Distance Gradient with various definitions of "CBD"



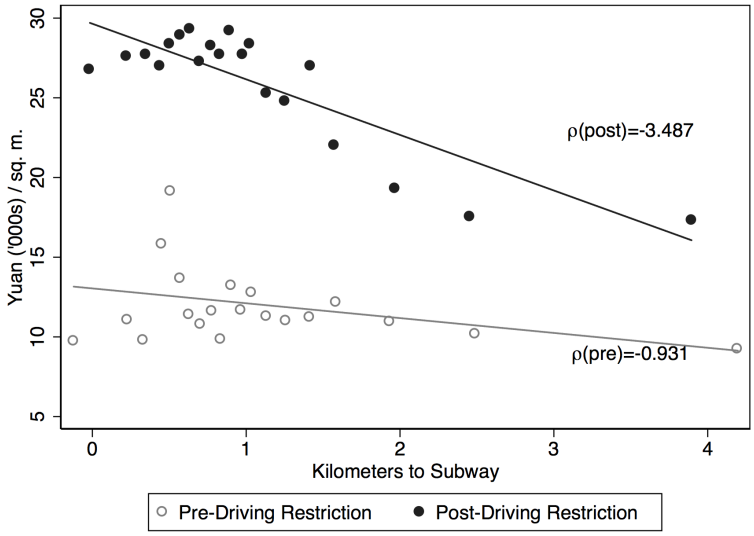
Note: Figure plots mean price per square meter by binned distance to city center. Includes 20 bins each with an average of 6,200 and 12,870 obs per bin in pre and post periods, respectively. Means residualized by distance to the nearest subway.

Figure A8: Evolution of Neighborhood Income Before vs After New Subway Station Openings



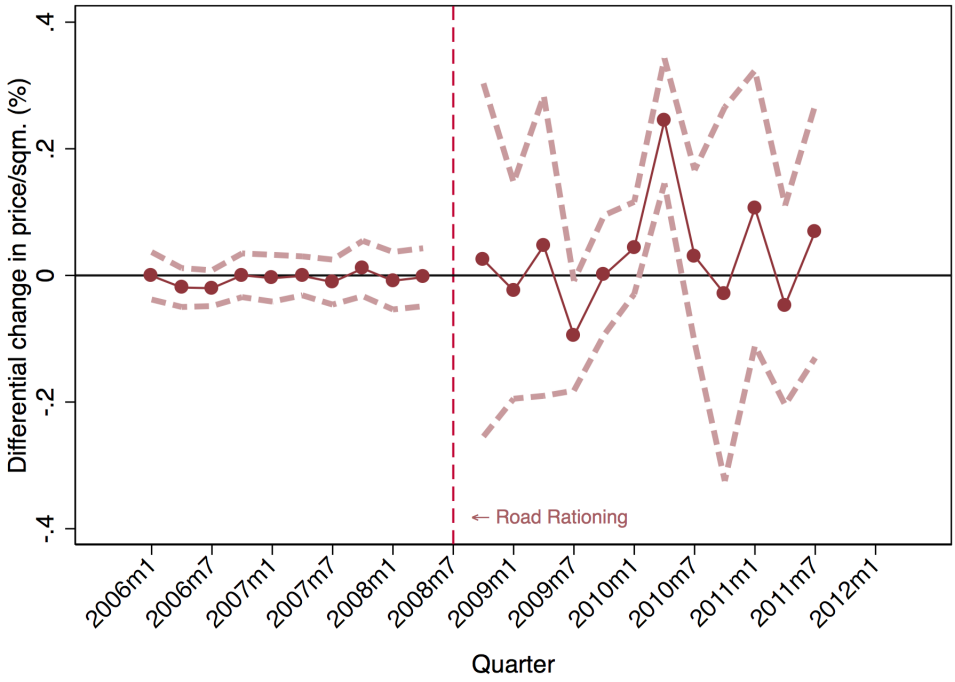
Note: Figure plots the difference in mean monthly household income in jiedao j in quarter q relative to quarter $q = 0$ when a subway station opens in jiedao j. Point estimates residualized by quarter-of-year fixed effects. Includes a balanced panel of 24 jiedao over 21 quarters. Sample spans 2005 through 2014 and includes 56 station openings. Bands show 95% confidence intervals. Source: Mortgage loan application data.

Figure A9: The Price-Distance Gradient and Beijing's Road Rationing Policy: Excluding Housing Near Newly-Built Stations



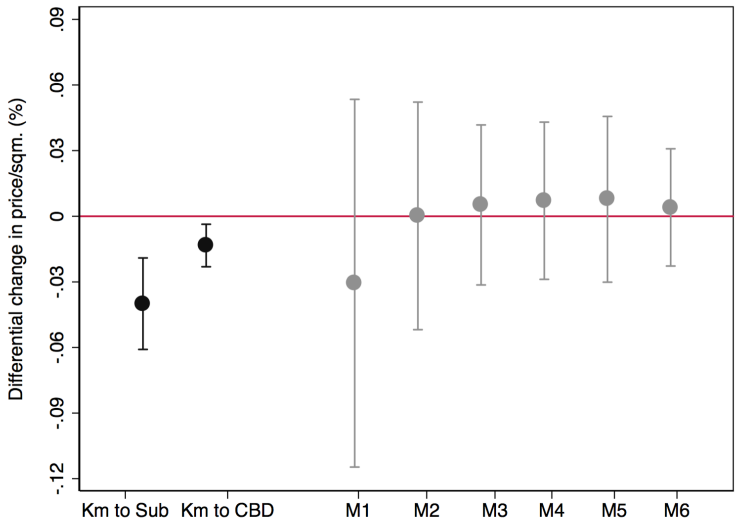
Note: Figure plots mean house price for each of 20 distance bins. Each dot represents 600 and 3,830 observations per bin in pre- and post- road rationing periods, respectively. Means are residualized by distance to the central business district. ρ(pre) and ρ(post) are regression coefficients. Includes years 2005-2016. Source: Real estate transaction dataset.

Figure A10: Placebo Effect of Road Rationing on the House Price-Subway Distance Gradient Among Housing over 3km from Station



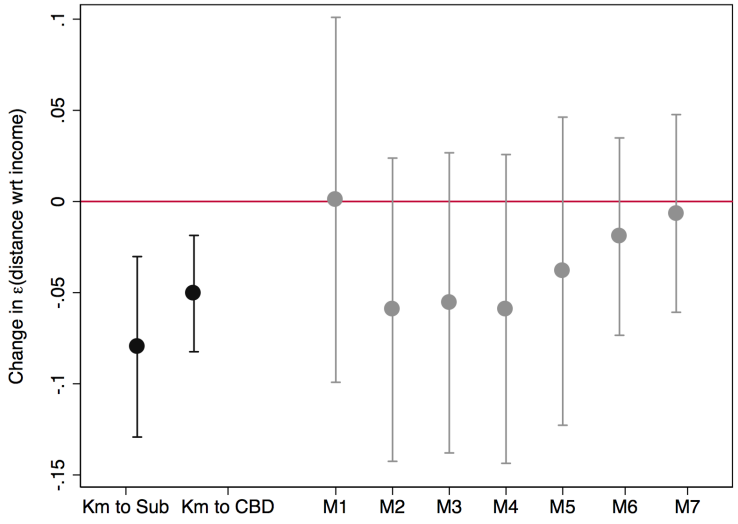
Note: Figure shows the partial effect of subway distance on housing price ln(total price/sqm in ¥2007) at each quarter between Jan 2006 and Dec 2011. The omitted quarter is July-October 2008. Dashed lines show 95% confidence intervals. Sample includes housing units located in building complexes that are over 3km from the nearest subway station through the event period; but are under 3km from a station after the event period ends (beginning in 2013). The sample includes 65,758 transactions. Controls include fixed effects for unit type (resale or newsale), jiedao, and year-quarter; as well as controls for distance to nearest CBD, age, age^2, size, floor-area ratio, green space, property management fee, parking fee, number of housing units and building units in complex, and unit size. Standard errors clustered at jiedao level.

Figure A11: Placebo Effect of Road Rationing on House Price-Distance to Pollution Gradient



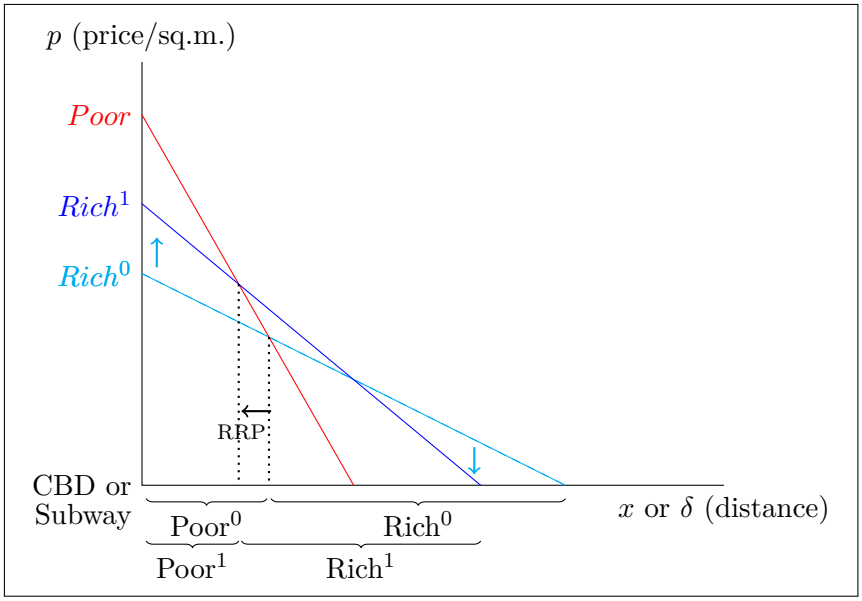
Note: Figure plots the effect of the road rationing policy on the housing price premium for distance to one of three locations: the first and second estimates in black show the road rationing effect for distance to a subway station and distance to a central business district, respectively. These estimates replicate column (4) in Tables 3 and 2, respectively. The gray dots show estimates of the road rationing effect for distance to a major pollution site under various specifications. All models include year and month fixed effects. Bands show 95% confidence intervals. Sample includes 82,002 transactions, spanning July 2007 through July 2009. Model "M2" adds jiedao fixed effects. "M3" adds controls for: unit type (resale or newsale), distance to nearest CBD (or subway in the CBD regression), age, age^2, size, floor-area ratio, green space, property management fee, parking fee, number of housing units and building units in complex, and unit size. "M4" adds year-by-month fixed effects. "M5" includes all controls as well as district by year-month linear time trends. Finally, "M6" includes all controls as well as complex fixed effects. Standard errors clustered at jiedao level.

Figure A12: Placebo Effect of Road Rationing on Distance to Pollution-Income Gradient



Note: Figure plots the effect of the road rationing policy on the elasticity of distance with respect to income. Distance is defined as kilometers to one of three locations: the first and second estimates in black show the road rationing effect for distance to a subway station and distance to a central business district, respectively. These estimates replicate column (6) in Table 5 and column (4) in 4. The gray dots show estimates of the road rationing effect for distance to a major pollution site under various specifications. All models include year and month fixed effects. Bands show 95% confidence intervals. Sample includes 18,414 transactions, spanning July 2006 through July 2010. "M2" adds neighborhood (zip code) fixed effects. "M3" adds controls for husband and wife age, employment rank, education, employer type, tenure, and distance to nearest CBD (or subway in the second estimate.) "M4" adds year-by-month fixed effects. "M5" includes all controls as well as district by year-month linear time trends. "M6" includes all controls, year-by-month fixed effects, and subway line fied effects. "M7" includes all controls, district by year-month linear time trends, and subway-line fixed effects. Standard errors clustered by neighborhood.

Figure A13: Urban Land Use and Equilibrium Sorting with Income Heterogeneity



Note: y-axis is price per square meter and the x-axis is distance from the CBD or a subway station, respectively. Location in the city is defined by x conditional on δ and vice verca. Each income group has a distinct bid-rent gradient. Let $\epsilon_{h,y} > \epsilon_{t,y}$ (i.e., income elasticity of housing > income elasticity of time costs). Consequently, the poor have a steeper gradient than the rich, *ex ante*. The road rationing policy (RRP) increases the cost of commuting for the rich, thus they increase their demand for locations proximate to both the CBD and subway stations, depicted as a tilt from $Rich^0$ to $Rich^1$. The RRP identifies $\frac{\partial p^2}{\partial x \partial (RRP)}$ and $\frac{\partial p^2}{\partial \delta \partial (RRP)}$. The RRP causes the price per square meter to increase for all units from the intersection of $Poor$ and $Rich^1$ to the intersection of $Poor$ and $Rich^0$. This also causes the rich to outbid the poor for units along the x-axis within the horizontal dotted lines.

Table A1: Effect of Road Rationing on Price-Distance to CBD Gradient-Varying Definition of CBD

	[CBD] =							
	Geographic Center	Technology District	Software District	Financial District	Beijing "CBD"	Embassy District	Business District	Commercial District
Km to [CBD] x CDR	-0.007	-0.008***	-0.007***	-0.009*	-0.006**	-0.005	-0.006**	-0.010**
	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.004)	(0.002)	(0.005)
Km to [CBD]	0.023	0.020	0.015	0.036**	0.006	0.005	0.007	0.021
	(0.017)	(0.012)	(0.012)	(0.017)	(0.013)	(0.014)	(0.013)	(0.017)
Year & Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Jiedao FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Avg Price Premium / Km	$633.04	$695.82	$630.24	$727.10	$537.56	$404.06	$484.61	$857.16
Observations	82002	82002	82002	82002	82002	82002	82002	82002
Adjusted R^2	0.609	0.609	0.609	0.610	0.608	0.607	0.608	0.609

Note: Dependent variable is ln(total price per square meter in 2007 real Yuan). Standard errors clustered at jiedao level. Sample spans 12 mos. before and after CDR. Average price premium is evaluated at a unit size of 122 sqm, the size at the mean distance to the nearest business district (5 and 7 km), and at a conversion rate of 6.95 yuan per USD. Controls include fixed effects for unit type (newsale vs resale), top floor, floor level, facing direction, no. bedrooms, decoration level, ownership type, and total number of floors in building. Continuous controls include distance to nearest subway station, age, age2, size, floor-area ratio, green space, property management fees, parking fees, and size, number of housing units and number of buildings of the complex. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Comparison of CDR Effects with Xu et al. (2015)

	CDR is October 11				CDR is July 20			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Distance to Subway)	-0.081**	0.071	-0.022	-0.085**	-0.096**	0.010	-0.057***	-0.124**
	(0.038)	(0.049)	(0.023)	(0.039)	(0.038)	(0.057)	(0.019)	(0.050)
Ln(Distance to Subway) x CDR	-0.069	-0.107***	-0.068***		-0.085	-0.077**	-0.049***	
	(0.049)	(0.030)	(0.023)		(0.055)	(0.031)	(0.013)	
Location Controls	Y			Y	Y			Y
Full Controls			Y				Y	
Jiedao FE		Y	Y			Y	Y	
6 mos. pre CDR				Y				Y
Observations	18989	18981	18981	5917	14061	14051	14051	6016
Adjusted R^2	0.223	0.630	0.720	0.166	0.189	0.654	0.731	0.101

Note: Dependent variable is ln(total price per square meter in 2007 real Yuan). Standard errors clustered at building complex level. Excludes housing units near newly built subway stations. Location Controls include distance to city center, and an indicator for locating within a key school district. Controls include year, month, and district fixed effects; and controls for complex age, age2, size, floor-area ratio, green space, no. total floors; controls for housing unit size, decoration level, floor level, facing direction, and no. bedrooms. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Effect of Road Rationing on Distance to CBD-Income Gradient-Varying Definition of CBD

	Geographic Center	Technology District	Software District	Financial District	Beijing "CBD"	Embassy District	Business Park	Shopping District
Ln(Household Income)× CDR	-0.010**	0.002	-0.009**	0.002	-0.020***	-0.015***	-0.021***	-0.011***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
Ln(Household Income)	-0.001	-0.011**	-0.003	-0.009**	0.009**	0.003	0.009*	0.000
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Year & Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Subway Line FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	18135	18135	18135	18135	18135	18135	18135	18135
Adjusted R^2	0.979	0.957	0.959	0.980	0.967	0.972	0.963	0.978

Note: Dependent variable is ln(Distance to CBD (km)). Income is household monthly income ('000 yuan). CDR equals 1 after July 20 2008. Standard errors clustered by zip code. Sample spans July 20, 2006-July 20, 2010. Controls include distance to nearest subway, husband and wife age, employment rank, education, employer type, and tenure. Subway Line FE is a fixed effect for the subway line associated with the housing unit's closest subway station. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effects of Road Rationing on House Price-Distance Gradient, Excluding Houses Near Newly-Built Stations

	(1)	(2)	(3)	(4)	(5)	(6)
Km to Subway x CDR	-0.020	-0.022***	-0.024***	-0.012***	-0.027***	-0.024***
	(0.019)	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)
Km to Subway	-0.109***	-0.053***	-0.043***	-0.049***	-0.040**	
	(0.015)	(0.009)	(0.015)	(0.015)	(0.016)	
Controls		Y	Y	Y	Y	Y
Jiedao FE			Y	Y	Y	Y
Year-Month FE				Y		
DistrictxYear-Month Trend					Y	
Building Complex FE						Y
Avg Price Premium / Km	$1694.84	$1902.35	$2062.51	$1005.90	$2324.19	$2040.08
Observations	12474	12474	12474	12474	12474	12147
Adjusted R^2	0.191	0.635	0.731	0.741	0.732	0.801

Note: Dependent variable is ln(total price per square meter in 2007 real Yuan). Sample includes housing units in building complexes that do not change in their proximity to subway stations from 2005 through 2016. Standard errors clustered at jiedao level. Sample spans 12 mos. before and after CDR. All specifications include year and month fixed effects. Average price premium is evaluated at a unit size of 115 sqm, the size at the mean distance (between 2 and 4 km) to the nearest subway station, and at a conversion rate of 6.95 yuan per USD. Controls include fixed effects for unit type (newsale vs resale), top floor, floor level, facing direction, no. bedrooms, decoration level, ownership type, and total number of floors in building. Continuous controls include distance to nearest CBD, age, age2, size, floor-area ratio, green space, property management fees, parking fees, and size, number of housing units and number of buildings of the complex. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Effects of Road Rationing on House Price-Distance to Subway Gradient - Controlling for Subway Network Density

	(1)	(2)	(3)	(4)	(5)	(6)
Km to Subway x CDR	-0.040*	-0.043***	-0.025**	-0.034***	-0.043***	-0.003
	(0.020)	(0.013)	(0.012)	(0.011)	(0.013)	(0.011)
Km to Subway	-0.042***	0.002	0.004	-0.009	0.008	-0.016
	(0.013)	(0.013)	(0.013)	(0.016)	(0.018)	(0.012)
Km to Subway x Network Density	-0.001	0.001	-0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Network Density	0.002	0.000	0.001	0.001	-0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Jiedao FE		Y	Y	Y	Y	Y
Controls			Y	Y	Y	Y
Year-Month FE				Y		
DistrictxYear-Month Trend					Y	
Building Complex FE						Y
Avg Proximity Premium / Km	$3232.07	$3525.87	$1978.90	$2793.64	$3522.48	$198.98
Observations	70307	70307	70307	70299	70307	69840
Adjusted R^2	0.161	0.518	0.485	0.586	0.512	0.809

Note: Dependent variable is ln(total price per square meter in 2007 real Yuan). Standard errors clustered at jiedao level. Sample spans 12 mos. before and after CDR. All specifications include year and month fixed effects. Average price premium is evaluated at a unit size of 115 sqm, the size at the mean distance (between 2 and 4 km) to the nearest subway station, and at a conversion rate of 6.95 yuan per USD. Controls include fixed effects for unit type (newsale vs resale), top floor, floor level, facing direction, no. bedrooms, decoration level, ownership type, and total number of floors in building. Continuous controls include distance to nearest CBD, age, age2, size, floor-area ratio, green space, property management fees, parking fees, and size, number of housing units and number of buildings of the complex. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B Derivation of the Bid-Rent Gradient

Residents face the following maximization problem. As in Section 3.1, the resident maximizes consumption of a numeraire good z with price of \$1 and consumption of housing h with price of p subject to a budget constraint. They receive income y from working. With that income, they pay for the numeraire good, housing, and commuting. Commuting costs ($w \cdot T(n, x, \delta)$) are the opportunity cost of forgone earnings w. Time spent commuting is a function of distance from the CBD x, the likelihood of using the subway n, and walking distance to the subway station δ.

$$\max_{z,h} U(z, h) \text{ s.t.} \tag{10}$$

$$z + ph + w \cdot T(n, x, \delta) = y$$

The transit time $T(n, x, \delta)$ differs depending on how likely an individual is to utilize the subway versus driving a car. The variable n ranges between 0 and 1 and measures the likelihood of commuting via subway. For the rich, n approximates zero because they are more likely to rely on cars to commute, except on road rationing days. Thus, we can define transit time as in Eq. 1 as follows:

$$T(n, x, \delta) = n\Big[\frac{\delta}{\omega} + \frac{x}{\sigma}\Big] + (1 - n)\frac{x}{\nu} \tag{11}$$

The first term in brackets encompasses transit time for commuting via subway: walking time to the station, which depends on the distance of the walk δ divided by walking speed ω and distance traveled on the subway to the CBD x divided by subway speed σ. The second term encompasses transit time to the CBD via car where car speed is ν. We assume car speed is greater than subway speed, which is greater than walking speed ($\nu > \sigma > \omega$).

In equilibrium, each resident i has achieved their highest utility subject to their budget constraint, and all residents have equal utility levels, $\max_{z,h} u_i = \overline{u}\ \forall i$. This is achieved by each resident optimally allocating their income between housing and commutes where, at each location of the city, they make a tradeoff between higher per-unit housing with lower commuting costs. Substituting the first budget constraint into Eq. 10, the equal utility condition is:

$$\max_{h} u_i(y - ph - T(n, x, \delta)w, h) = \overline{u} \forall i \tag{12}$$

Equations 10 and 12 are the two conditions required for equilibrium.

We derive the first order conditions of Eq. 10 by setting up a Lagrangian equation:

$$\mathcal{L} = u(z, h) + \lambda[y - ph - T(n, x, \delta)w - z]$$

The first derivative of $\mathcal{L}$ with respect to choice variables h and z are as follows:

$$\frac{\partial \mathcal{L}}{\partial z} = \frac{\partial u}{\partial z} - \lambda = 0 \rightarrow \frac{\partial u}{\partial z} = \lambda$$
$$\frac{\partial \mathcal{L}}{\partial h} = \frac{\partial u}{\partial h} - \lambda p = 0 \rightarrow \frac{\partial u}{\partial h} = \lambda p$$

Dividing the first condition by the second:

$$\frac{\partial u/\partial h}{\partial u/\partial z} = p \text{ or, equivalently } \frac{v_2}{v_1} = p$$

where v_1 denotes the partial derivative of the first argument in Eq. 10 and v_2 denotes that of the second argument.

Next, we totally differentiate Eq. 12 with respect to x to solve the system of equilibrium conditions:

$$v_1 \frac{\partial y}{\partial x} - v_1 \Big[\frac{\partial p}{\partial x} h + \frac{\partial h}{\partial x} p\Big] - v_1 \Big[\frac{\partial T}{\partial x} w + \frac{\partial w}{\partial x} T\Big] + v_2 \frac{\partial h}{\partial x} = 0$$

Since y and w do not vary with x, we are left with:

$$v_1 \Big[\frac{\partial p}{\partial x} h + \frac{\partial h}{\partial x} p\Big] + v_1 \Big[\frac{\partial T}{\partial x}\Big] w = v_2 \frac{\partial h}{\partial x}$$

From the first order conditions, we can substitute $\frac{v_2}{v_1} = p$, or $v_2 = v_1 p$ into the above equation:

$$-\frac{\partial T}{\partial x} w = \frac{\partial p}{\partial x} h \tag{13}$$

From Eq. 11, the left-hand side is equivalently:

$$-\Big[\frac{n}{\sigma} + \frac{1-n}{\nu}\Big] w = \frac{\partial p}{\partial x} h$$

Solving for the change in price with respect to distance from the CBD, we obtain the bid-rent function that demonstrates how housing prices fall with distance from the CBD at a rate proportional to the increased commuting costs required to reach the CBD from a distance x:

$$\frac{\partial p}{\partial x} = -\Big[\frac{n}{\sigma} + \frac{1-n}{\nu}\Big] \frac{w}{h} \tag{14}$$

which is Eq. 2 in the main text.

We similarly derive the bid-rent gradient for subway station proximity by totally differentiating Eq. 12 with respect to δ. Eq. 13 is instead:

$$-\frac{\partial T}{\partial \delta} w = \frac{\partial p}{\partial \delta} h$$

From Eq. 11, the left-hand side is equivalently:

$$-\frac{n}{\omega}w = \frac{\partial p}{\partial \delta}h \rightarrow \frac{\partial p}{\partial \delta} = -\frac{n}{\omega}\frac{w}{h}$$

which is Eq. 3 in the main text. Appendix Figure A13 graphically depicts $\frac{\partial p}{\partial x}$ and $\frac{\partial p}{\partial \delta}$. The same framework is applicable whether the origin is the central business district with distance x or a subway station with distance δ. Rich and Poor having different slopes, dictated by their respective cost of commuting and time value, as discussed in the text. This paper's empirical approach estimates the magnitude of the change in slope following the road rationing policy. In the simplified case of the Figure, we empirically estimate the slope change from $Rich^0$ to $Rich^1$.