The Role of Environmental Amenities in the Urban Economy: Evidence From a Spatial General Equilibrium Approach

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Abstract

Environmental amenities could play an important role in residential location decisions, which in turn affect the concentration of consumption and production activities. I develop and estimate a spatial general equilibrium model to examine how environmental amenities affect the spatial distribution of urban economic activities and the welfare consequences. The equilibrium model characterizes household location and consumption decisions as well as production decisions while incorporating agglomeration and dispersion forces. The empirical analysis leverages a natural experiment of pollution monitoring and information disclosure program and recovers key underlying parameters using fine-scale travel data on commuting and consumption trips and environmental amenities. The analysis shows that job access, residential amenities, and consumption access account for 49%, 30% and 21% of overall attractiveness of a residential location, respectively. Counterfactual simulations suggest a 8.4% welfare gain if households were to fully incorporate environmental amenities into their decisions, compared to the scenario of not incorporating environmental amenities. The welfare difference is driven by changes in residential and workplace locations as well as consumption and production decisions.

Keywords: Environmental amenities, location choice, consumption access, agglomeration

JEL Codes: D58, R21, R31, Q51

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1 Introduction

Environmental amenities could play an important role in residential location decisions, which in turn affect the concentration of consumption and production activities. Much of the current literature evaluating environmental amenities pays particular attention to their effects on one single product, such as housing, healthcare, or transportation, while few has been able to uncover the underlying mechanisms or pathways of impact. This paper aims to provide a comprehensive analysis to understand the effects of environmental amenities on the spatial distribution of urban economic activities and the welfare consequences. To do so, I develop and estimate a quantitative spatial general equilibrium model that characterizes household location and consumption decisions as well as production decisions while incorporating agglomeration and dispersion forces.

The empirical context of my study is the central area of Beijing within its 6th ring road, with a land area of around 3,000 square kilometers and a population of more than 15 million. The study area is densely populated and hosts a majority of the city's service production and consumption. The area is also the center of Beijing's transportation networks where most commuting and consumption travels concentrate. From 2010 to 2014, Beijing, among other major cities in China, implemented a series of air pollution monitoring and information disclusure programs. As a result, the city witnessed drastic changes in consumer behaviors due to increasing public awareness and information access (Ito and Zhang, 2018; Tu et al., 2020; Barwick et al., 2020). I use the implementation of the program as a natural experiment and quantify consumers' preference change during the period. With reduced form estimations, I document that the program led to substantial changes in the valuation of environmental amenities in the housing markets. I then simulate multiple counterfactual scenarios using the structural model to evaluate the welfare impacts if individuals were to fully incorporate environmental amenities into their decisions, compared to the scenario of not incorporating environmental amenities.

The empirical analysis leverages the spatial granularity of a rich data set on residential locations, commuting and consumption trips, housing transactions, and environmental amenities. The main data set is from the Beijing Household Travel Survey (BHTS), conducted in 2010 and 2014.

The surveys gather information on household and individual demographics as well as travel diaries documenting the trips each individual made in a 24-hour time frame preceding the survey. I complement this data set with a transaction sample of new and existing homes from 2006 to 2014 to construct housing prices for each location. I gather fine-scale data on air pollution and green space from satellite imagery. Locations of non-environmental amenities including schools and hospitals are collected as controls.

With this data set, I develop and estimate a spatial general equilibrium model that characterizes household location and consumption decisions as well as production decisions while incorporating agglomeration and dispersion forces. From the estimated equilibrium outcomes, I recover the contribution of job access, residential amenities, and consumption access in the overall attractiveness of a residential location. I estimate a composite measure for unobserved residential amenities and decompose it into locations' environmental and non-environmental attributes. The model is calibrated for 2010 and 2014 to capture consumers' preference change. Finally, I conduct a counterfactual analysis by imposing consumers' preferences on environmental amenities in 2014 to their 2010 decisions and simulate the equilibrium outcomes if consumers had fully incorporated environmental amenities into their decisions. Additional scenarios are estimated to uncover the channels of the welfare impact and consumers' marginal compensation for lack of environmental amenities.

My analysis yields three key findings. First, the estimates show that job access, residential amenities, and consumption access account for 49%, 30% and 21% of overall attractiveness of a residential location, respectively. This is to my knowledge the first study documenting factors affecting consumers' residential location choices for a city in a developing economy like Beijing. Residential amenities play a larger role for consumers' residential decisions in Beijing, compared to other developed cities examined in the literature, such as Tokyo and Singapore. Access to consumption and service locations are comparatively less important in determining residential attractiveness in Beijing, mirroring its residents' smaller expenditure share on services than those in the developed economies.

Second, I document a stronger emphasis on locations' environmental attributes when consumers in Beijing selected residence in 2014 compared to 2010. Specifically, I find no statistically significant link between the estimated residential amenity and locations' environmental qualities in 2010, indicating their possible absence from the residents' decision process. Conversely, the re-calibrated results using parameters and data sets from 2014 feature a significant positive correlation between a location's environmental characteristics and its estimated level of residential amenity. This is consistent with findings in Barwick et al. (2020) where they document in Beijing's housing market that the capitalization of local air pollution was suppressed in 2010 and only introduced after the roll-out of pollution monitoring and information disclosure programs.

Third, my analysis reveals large welfare benefits if consumers were to incorporate environmental amenities into their decisions, compared to the scenario of not incorporating environmental amenities. Estimates from the counterfactual practice suggest that the incorporation of environmental amenities into consumers' decision utility would lead to a 8.43% increase in the overall welfare compared to the original equilibrium levels observed in 2010. This is equivalent to the welfare change of imposing a 8.43% raise in income for all individuals, while holding all other variables at their unadjusted levels. For 2010, the welfare benefit translates to 2,450 Chinese *yuan* (or \$366 in 2010 dollars, \$440 in 2021 dollars) per person. With a 20-million population, the total benefit for Beijing's residents adds up to 50 billion *yuan*. Further analysis attributes the welfare gain mostly to changes in residential and workplace locations as well as consumption and production decisions. For locations in the most polluted quartile (with an annual $PM_{2.5}$ concentration above 75 $\mu g/m^3$), the counterfactual analysis predicts an 18% drop in the number of residents and a 7% drop in the number of workers on average, due to industrial and production relocation. Residents there would need to have a higher income in equilibrium to compensate for the low air quality, for which the model predicts a 3% increase in residential income and workers' average wage. Decline in housing demand for both residential and production use would lead to a 12% decrease in area of floor space and a 5% decrease in housing prices for the most polluted neighborhoods at the new equilibrium.

My study makes several contributions to the literature. First, this paper is among the first to provide a comprehensive estimate on the welfare impacts of environmental amenities using a quantitative urban model that captures multiple margins from different sectors and locations in an urban system. Previous evaluations on environmental amenities based on consumers' revealed preferences rely mostly on one single sector, such as healthcare and housing[1]. While each strand of literature offers valuable insights on how environmental amenities affect consumer decisions on the respective product, the underlying mechanism through which the impacts are channelled remains understudied. Models adopted in the sorting literature does allow for a decomposition of multiple margins with simulations, though the estimation in essence still builds upon partial equilibrium outcomes (Epple and Sieg, 1999; Bayer et al., 2009; Kuminoff et al., 2013). Among the few studies that use general equilibrium models in an effort to recover economy-wide estimates (Carbone and Smith, 2008, 2013; Rudik et al., 2021), most of them use models that are spatially coarse and treat for example the U.S. or its states as the basic units of analysis. My paper contributes to this literature with a tractable spatial general equilibrium framework that can provide comprehensive welfare estimates while remaining separable as to examine which sectors or locations are primarily impacted by the proposed change in preference. This is made possible as the model in this paper, at the neighborhood level, rationalizes the supply and demand in multiple local markets, and at a regional level, incorporates cross-neighborhood interactions from consumers' location choices.

Methodologically, this paper is closely related to and builds on Miyauchi et al. (2020) and Tan and Lee (2020). Both papers evaluate the welfare impacts from improved inter-neighborhood mobility, a traditional focus of the quantitative urban literature (Allen and Arkolakis, 2014; Redding, 2016; Desmet et al., 2018; Monte et al., 2018; Allen and Arkolakis, 2019). This paper compliments the urban literature by providing the first decomposition of locations' residential attractiveness for a city in an developing economy. The decomposition analysis also establishes the role of environmental amenities in urban economic activities. This paper is also the first to calibrate the quantita-

[1]For example, studies based on averting behavior methods draw estimates from healthcare spending (Williams and Phaneuf, 2016; Deschênes et al., 2017; Barwick et al., 2018; Deryugina et al., 2019) or defensive expenditures (Mu and Zhang, 2016; Sun et al., 2017; Ito and Zhang, 2018); conventional analysis under the hedonic pricing framework focuses on sorting outcomes in the real estate market (Epple and Sieg, 1999; Chay and Greenstone, 2005; Bayer et al., 2009; Banzhaf and Walsh, 2008; Kuminoff et al., 2013; Gao et al., 2021); the travel cost method imputes the value of amenities leveraging the trade-off between recreational demand and travel costs (Clawson and Knetsch, 1966; Parsons and Stefanova, 2011; Parsons et al., 2013; Mude et al., 2020).

tive urban model using detailed travel surveys with clearly-stated travel purposes, location choices, and individual demographics, which are not available for previous studies using smartphone GPS or public transportation data sets. Moreover, my study expands the application of the model and illustrates how changes in consumer preference of a local amenity, or the provision of the amenity itself, can also have non-local effects that can ripple through an urban system and reshape the spatial distribution of residents and production activities. This paper demonstrates that the quantitative spatial model are capable of provide theoretically consistent predictions under various simulated scenarios, which potentially have important policy implications. Such policies and interventions include but are not limited to pollution information disclosure programs, news reports on environmental hazards, development of urban projects, relocation of firms or government offices, etc.

The remainder of the paper is organized as follows. Section 2 describes the main data sources. Section 3 presents the reduced form evidence on the valuation of environmental amenities in housing prices. Section 4 introduces the a spatial urban model that evaluates the role of environmental amenities in a general equilibrium framework. Section 5 estimates the model parameters. Section 6 conducts counterfactual analysis for the impact of environmental amenities on welfare and spatial distributional effects.

2 Background and Data

2.1 Air Pollution Monitoring and Information Disclosure in Beijing

Beijing was among the first wave of 42 Chinese cities that established infrastructures for air pollution monitoring in 2000 (*People's Daily Online*, 2000). In the same year, China's Ministry of Environmental Protection started publishing daily air pollution index (API) at the city level through the National Daily Report on Air Quality. Official air pollution data in the following decade was limited in both temporal and spatial resolution and rarely receive public attention.

In 2008, the U.S. Embassy in Beijing started monitoring $PM_{2.5}$ concentrations from its rooftop sensors and published the hourly readings real-time on Twitter. The inconsistency between monitored data from these sensors and the government sources was propelled into a public debate during episodes of extreme pollution in late 2011 and even raised diplomatic tension.

Large-scale real-time air pollution monitoring was first implemented in Beijing on Jan. 21, 2012 (*People's Daily Online*, 2012), when 27 monitoring stations across the city started collecting hourly readings for pollutants including SO_2, NO_2 and particulate matter (PM_{10}).[2] Air pollution data was streamed to the public through MEP's website and was soon adopted by many pollution and weather apps. The air pollution monitoring-and-disclosure program started to roll out to other major Chinese cities in 2013 and finally adopted nationwide in 2015, marking a watershed moment in the history of China's environmental regulations.

The pollution information program also sparked attention of the mass media, leading to multiple high-profile coverage on air pollution issues. Jointly, they stimulated substantial changes in public awareness and consumer behaviors, as captured in the literature through housing markets outcomes (Barwick et al., 2020), defensive spending (Ito and Zhang, 2018), willingness to pay for clean air (Tu et al., 2020), etc. I show in Section 3 how the capitalization of air quality has changed in Beijing's housing market with the program's implementation.

2.2 Commuting and Travel Data

I collect data on consumer's residential, workplace, and consumption location choices from two rounds of the Beijing Household Travel Survey (BHTS). The surveys are conducted in 2010 and 2014 by the Beijing Transportation Institute, a research agency affiliated with the city's municipal government. The surveys' original design is to inform on urban transportation development. The surveys collect repeated cross-sectional data through in-person interviews on household and individual demographics (e.g. household income, size, home and car ownership, age, gender, occupation, etc.) as well as a travel diary for each household member. The travel diary covers all trips taken in a 24-hour time frame preceding the survey and includes information on the origin and destination, departure and arrival time, purpose of the trip and travel mode used. The surveys for

[2]In 2013, the monitoring system was modified to include fine particulate matter ($PM_{2.5}$) and implemented tighter standards.

each year cover roughly 0.5% of Beijing's residents.

I define the study area to be the center of Beijing within its 6th ring road, with a land area of around 3,000 square kilometers and a population of more than 15 million in 2010. This area is densely populated and hosts a majority of the city's service production and consumption activities. This area is also the core of Beijing's transportation networks and concentrates most of the commuting and consumption travels in the city. I cover the area using a 2×2 km grid, with the grid cells being the basic location units in my spatial analysis. There are 756 cells in total.[3]

I aggregate individual choices on residential locations, workplace, and consumption location to the cell level and derive the probability of a cell's residents visiting other locations for each purpose of travel. I impute individual income using household income averaged over the full-time equivalent labor units within the household[4]. Table 1 provides summary statistics on the demographics of the surveyed individuals who are in employment in 2010.

Spatial Patterns Figure 1 shows the spatial patterns of the survey data. I plot the residential density, worker density, average residential income, and average wage for each location. The sample of the survey is spatially representative. The residential density from the surveyed sample are closely correlated with population density estimated by the Chinese Academy of Science (CAS) and NASA, as shown in Figure A1[5]. The density maps reveal Beijing's strong monocentric characteristics, with a very large residential and employment center at its core, and a few smaller centers along the west-east axis and in the suburban districts. Moreover, the study area features a distinctive north-south divide. The northern half of the city has more high-income neighborhoods and high-wage workplaces than the south. To further explore the divide, I plot in Figure A2 the net inflow of commuters for each location, calculated as the difference between residential and worker density. Red cells in the map denote locations that has more jobs than residents and therefore relies on commuters from other locations as labor inputs for local firms; cells in blue has more residents

[3]The size of the grid cells are defined such that the grid is not too coarse, so that spatial heterogeneity and inter-neighborhood travel patterns are preserved, nor overly fine, so that the survey sample is still spatially representative with few missing values.

[4]I designate full-time employees a weight of 1 and part-time a weight of 0.5

[5]The cell-level correlation between the residential density of survey and of CAS or NASA is above 0.8.

than workers and provide labor force to other locations through commuting. Again, the commuting map shows an uneven distribution of employment and residents, where business centers locates predominantly in locations north of the axis road, and the southern areas are more residential.

Commuting and Consumption Trips Besides the spatial characteristics of the trip, the survey data also records self-reported trip purposes, such as commuting to work or school, shopping, dining, etc. This allows me to distinguish between commuting and consumption trips and later identify the determinants of residential decisions in Section 5.3.

Commuting trips account for the largest proportion of individuals' daily travel, taking up approximately half of all trips recorded in the surveys. Consumption trips, which I define as the collection of shopping and dining trips, are the second largest category and make up for 20% of all travels. Previous literature has highlighted that consumption trips differ from commuting trips in many characteristics (Miyauchi et al., 2020; Tan and Lee, 2020). I show in Figure A3 the trip distance for commuting and consumption trips. Since the data set do not have information on the route of the trip, I define trip distance as the direct distance between the origin and destination of the travel. The consumption travels in Beijing are shorter in distance, with an average of 3.6 kilometers, compared to commuting trips' 7.4 kilometers. Figure A4 reports the same pattern in travel time. On average, time spent on travel is almost linear to the trip distance (Figure A5). In the empirical analysis, I use the geographical distance of two locations to estimate travel cost as it is exogenous of travel mode selections. Duration of stays at consumption locations is also much shorter than stays at workplaces, as shown in Figure A6.

Other popular reasons for travel include fitness and exercise, school and classes, picking up people, and other personal businesses. A majority of these trips are made by children or the retired, whose residential and consumption decisions may depend on other household members in employment. I exclude these cohorts from my analysis and focus only on the trips made by the employed population.

2.3 Air Quality

I use satellite-derived $PM_{2.5}$ data covering the time periods of the surveys for Beijing from Hammer et al. (2020) and Van Donkelaar et al. (2019). The data set includes estimated annual average concentration of $PM_{2.5}$ at a high resolution of 0.01° and is recently re-calibrated with monitored data from China's expanded $PM_{2.5}$ measurement network. The pollution data is aggregated to 2×2 km cells using within-cell averages. I plot in Figure A8 the air pollution level for each cell in 2009, one year before the 2010 travel survey[6]. The figure shows that the central part of Beijing within the 5th ring road experiences the worst pollution in the city, averaging over 76 $\mu g/m^3$ in annual $PM_{2.5}$ concentration. The polluted area extends from the city center to the southern neighborhoods, while the northwest and northeast corners of the study area enjoys relatively clean air. This can be explained by Beijing's location at the northern tip of a polluted city cluster, with heavy industry plants to its south and mountains to its north.

2.4 Housing and Floor Space

I collect data on housing transactions sourced from two major real estate firms in Beijing. Data for each transaction includes the latitude and longitude of the housing unit, the transaction price, and characteristics of the housing unit and the complex that the unit belongs to. The data set includes 772,419 transactions for both new and resale homes from 2006 through 2014. Locations of these housing units are plotted in Figure A7.As the data set is a sample from the universe of housing transactions, I reweight the transactions using the total number of new and resale homes sold in each year published by Beijing Municipal Commission of Housing and Urban-Rural Development. The transactions are then aggregate to the cell level according to the geographical location of the housing units.

The production sector also has a demand for floor space. I additionally derive production floor space from residential income, consumption probabilities, and residential housing price, assuming perfect competition in the production sector and zero adjustment cost between residential and

[6]In the model estimation, I lag air pollution by one year to avoid any endogeneity concerns due to simultaneity.

production floor space.

In Figure 1, I map the floor space density and the average housing prices in 2010. The spatial distribution of floor space roughly matches those of residents and production activities in the city, which are the two sources of demand for floor space. Housing prices are notably higher in the city center, and the northern half of the city hosts more expensive housing units than the south on average.

2.5 Other Residential Amenities

I collect data on the locations of schools, hospitals, and parks, as plotted in Figure A9. I construct three proximity indices using inverse distance weighting to measure each location's access to the city's schools, hospitals, and parks. For example, residence n's proximity index to schools is constructed as

$$index_n^{school} = \sum_{j \in J} \frac{1}{dist_{nj}} q_j,$$

where J denotes the set of schools; d_{nj} denotes the distance between residence n and school j; q_j denotes the quality of the school[7]. Proximity indices to hospitals and parks are constructed similarly. I categorize locations' access to parks as an environmental amenity (in addition to air quality), and access to schools and hospitals as non-environmental amenities.

3 Reduced Form Evidence

Before proceeding to the general equilibrium model, I examine the impact of environmental amenities on equilibrium prices in the housing market. I use Beijing's implementation of the pollution monitoring and information disclosure programs in 2012 as a natural experiment.

In Figure 2, I plot the relationship between air pollution and housing price per unit area from the housing transactions in Beijing. I control for variables including cell fixed effects, transaction year-

[7]For schools and hospitals, the amenity qualities are fixed at 1; for parks, I treat each cell as a potential amenity provider (j) and use the area of green space in each cell as the quality measure (q_j).

month fixed effects, quadratic functions of unit and complex size, as well as other unit and complex characteristics (such as number of rooms, distance to nearest subway station at transaction date, school district, complex size, and number of buildings). The blue dash line in the graph denotes the semi-elasticities of housing price with respect to air pollution for each quarter, and the gray area denotes the 95% confidence interval of the estimates. The semi-elasticities are estimated from the following specification,

$$\log UnitPrice_{int} = \sum_{q} \alpha_q poll_{nt} + \mathbf{z}'_{int}\beta + \eta_n + \xi_t + \varepsilon_{int}$$

where $UnitPrice_{int}$ denotes the unit housing price in a transaction i for a housing unit located in cell n in year-month t; q denotes the year-quarter and α_q are the quarterly semi-elasticities; $poll_{nt}$ is the cell's pollution level; $\mathbf{z}_{int}$ is the property charactristics introduced above; η_n and ξ_t are the location and transaction year-month fixed effects, respectively.

The semi-elasticities of housing price are small and insignificant before Beijing implemented the pollution monitoring-and-disclosure programs in 2012, indicating a limited response of the housing market to air pollution. From the first quarter of 2012, I document a negative and statistically significant relationship between housing price and the location's air pollution level. The estimates show a much stronger capitalization of air quality in housing market outcomes after the implementation of the pollution monitoring-and-disclosure program, consistent with findings from the literature. More importantly, the drastic change in the event-study estimates at the first quarter of 2012 is evidence that the changes in consumer preference are not driven by increased income, since there are no sharp changes in residential income at the beginning of 2012. My findings corroborate results from Barwick et al. (2020), where they leverage the staggered roll-out of the monitoring-and-disclosure program at a national scale, controlling for income levels, and document evidence of consumers' changing preference due to the information program.

In the next sections, I propose and estimate a general equilibrium framework that uncovers how environmental amenities and consumer awareness affect market outcomes in multiple sectors.

4 Theoretical Framework

In this section, I present a spatial general equilibrium model that characterizes household location and consumption decisions as well as production decisions while incorporating agglomeration and dispersion forces. I model the city as a collection of locations that differ in residential amenity, productivity, quality of service, and costs of travel to other locations. I specify a closed-city model with exogenous total population that abstract away migration in and out of the city. Individuals choose their residence, workplace, and consumption location among the locations in the city, and then choose a consumption bundle consisting of tradable goods, residential housing, and non-tradable goods (services). Individuals have Cobb-Douglas utility and derive utilities from the consumption bundle as well as local residential amenities. I model two production sectors, the service sector and the construction sector, both featuring competitive markets and constant-returns-to-scale technology. The service sector produces non-tradable goods using labor and floor space as inputs to meet the service demand from local and non-local consumers. Labor input of the service sector in any given location is supplied by the location's residents who choose to work in local firms and commuters from other locations. The construction sector produces floor space from land and capital to meet local residential and production demands. Transport of tradable goods is costless across the city, and the price of tradable goods are the same at all locations. Consumers and producers take wage and prices as given when making decisions. Markets at each location clear at equilibrium price and wage levels. Figure 3 summarizes the framework of the model.

4.1 Consumer's Problem

The utility function for an individual, i, takes the Cobb-Douglas form below.[8] Individual i resides in location n, works in location m, and consumes non-tradable goods in location j.

$$
\begin{aligned}
U_{nmj}(i) = & B_n b_n(i) \left[\frac{x_T(i)}{\alpha_T}\right]^{\alpha_T} \left[\frac{H(i)}{\alpha_H}\right]^{\alpha_H} \left[\frac{x_S(i)d_j(i)}{\alpha_S}\right]^{\alpha_S}, \\
& \text{and } 0 < \alpha_T, \alpha_H, \alpha_S < 1, \\
& \alpha_T + \alpha_H + \alpha_S = 1,
\end{aligned} \tag{1}
$$

where $x_T(i)$, $H(i)$, and $x_S(i)$ denote the level of consumption for tradable goods, residential housing, and non-tradable goods (services), respectively, that jointly define the consumption bundle ; α_T, α_H, and α_S are the preference weights. B_n is the common level of amenity appreciated by all residents in location n. $b_n(i)$ is the idiosyncratic amenity draw for individual i that is specific to a potential residence choice n. $d_j(i)$ is the idiosyncratic draw on the individual i's perceived quality of non-tradable goods at a potential consumption place j.

Combining consumers' preferences with their budget constraints, I specify consumers' utility maximization problem as

$$
\begin{aligned}
& \max_{\{x_T(i), H(i), x_S(i)\}|n,m,j} U_{nmj}(i), \\
& \text{s.t. } P_{nT}x_T + P_{nH}H + P_{jS}\kappa^S_{nj}x_S \leq \frac{a_m(i)w_m}{\kappa^W_{nm}} \\
& \text{where } 0 < \alpha_T, \alpha_H, \alpha_S < 1, \\
& \alpha_T + \alpha_H + \alpha_S = 1,
\end{aligned}
$$

where P_{nT}, P_{nH}, and P_{jS} define price vectors, w_m is the average wage for an efficiency unit of labor at workplace m, and $a_m(i)$ is the idiosyncratic productivity shock received by worker i for a specific workplace m. κ^W_{nm} denotes the bilateral iceberg travel cost incurred by an individual commuting

[8]Individual decision makers in the consumer's problem also make choices on residence and workplace. I use the terms individuals, consumers, residents, and workers interchangeably in the following sections, depending on the focus of the specific problem.

from n to m for work, and κ_{nj}^{S} denotes the travel cost for consumption trips from n to j. The total budget for individual i is the wage that the worker receives ($a_m(i)w_m$) discounted by the commuting cost (κ_{nm}^{W}) to rationalize consumers' distaste for lengthy commuting trips. Likewise, κ_{nj}^{W} effectively inflates the service price that consumers receive if they seek services from a non-local provider.

There are three individual-specific random draws in the consumer problem, $b_n(i)$, $a_m(i)$ and $d_j(i)$. They each capture individuals' idiosyncratic tastes for residence, workplace and consumption location, that are not explained by common amenity, wage, prices, or travel costs. In the model, I define the shocks $b_n(i)$, $a_m(i)$ and $d_j(i)$ as amenity shocks, productivity shocks, and quality of service shocks as a simplification, since these are the major factors affecting consumers' idiosyncratic location preference. The idiosyncratic shocks follow independent Fréchet distributions,

$$
\begin{aligned}
&F_n^B(b) = \exp(-T_n^B b^{-\theta_B}),\\
&F_m^W(a) = \exp(-T_m^W a^{-\theta_W}),\\
&F_j^S(d) = \exp(-T_j^S d^{-\theta_S}),\\
&\text{where } T_n^B, T_m^W, T_j^S > 0, \text{ for any } n, m, j \in N,\\
&\qquad \theta_B, \theta_W, \theta_S > 1.
\end{aligned}
$$

T_n^B, T_m^W, and T_j^S are the scale parameters that determine the overall level of random draws for each location. θ_B, θ_W, and θ_S are the dispersion parameters that govern the variations in random draws across individuals. The dispersion in consumers' individual tastes on amenities, services, and in the levels of productivity allows consumers with identical utility structure to make different choices that maximize their utilities with respect to different random draws. At an aggregated level, this heterogeneity in decisions are featured in population's choice probabilities.

Individuals make decisions in the following sequence[9]:

Step (1) Individual i chooses residence, after observing idiosyncratic amenity draws $b_n(i)$;

Step (2a) Individual i chooses workplace, after observing idiosyncratic productivity draws $a_m(i)$, con-

[9] I take residential location choice as the first step, since more than 90% of the travels are round trips that start and end from individual's home locations.

ditioning on residence n;

Step (2b) Individual i chooses consumption place, after observing idiosyncratic service quality draws $d_j(i)$, conditioning on residence n;

Step (3) Individual i choose the optimal consumption bundle of tradable goods, residential housing, and non-tradable goods, conditioning on previous choices: residence n, workplace m, and consumption place j.

As I define in the decision sequence, individual i facing a residential decision in Step (1) do not have information on the realization of idiosyncratic draws , $a_m(i)$ and $d_j(i)$. Decisions on workplace in step (2a) and those on consumption place in (2b) are independent of each other; they are therefore synchronous and interchangeable in the timing sequence.

Optimal consumption bundle. I solve the consumer's problem using backward induction, starting from the last step where consumers chose the optimal consumption bundle for given locations n, m, and j. Deriving from the Cobb-Douglas utility function in Equation 1, the optimal levels of consumption on goods and services for individual i are

$$\begin{aligned} x_T(i) &= \frac{a_m(i)w_m}{\kappa_{nm}^W}\frac{\alpha_T}{P_{nT}}, \\ H(i) &= \frac{a_m(i)w_m}{\kappa_{nm}^W}\frac{\alpha_H}{P_{nH}}, \\ x_S(i) &= \frac{a_m(i)w_m}{\kappa_{nm}^W}\frac{\alpha_S}{P_{jS}\kappa_{nj}}. \end{aligned} \tag{2}$$

where the individual spends an α_T, α_H, and α_S proportion of income on the three sectors, respectively.

Insert the optimal bundle back into the utility function, and I can evaluate the indirect utility as

$$V_{nmj}(i) = \frac{B_n b_n(i)}{P_{nT}^{\alpha_T} P_{nH}^{\alpha_H}} \cdot \frac{a_m(i)w_m}{\kappa_{nm}^W} \cdot \left[\frac{d_j(i)}{P_{jS}\cdot\kappa_{nj}^S}\right]^{\alpha_S}.$$

The first fraction in the indirect utility, $\frac{B_n b_n(i)}{P_{nT}^{\alpha_T} P_{nH}^{\alpha_H}}$, depends solely on characteristics of the residential location n, such as amenities and prices of locally-consumed goods. The second fraction, $\frac{a_m(i) w_m}{\kappa_{nm}^W}$, is the consumer's effective income in the budget constraint; it is driven by the consumer's workplace choice m alone, conditioning on residence n. The third part of the indirect utility, $\left[\frac{d_j(i)}{P_{jS} \cdot \kappa_{nj}^S}\right]^{\alpha_S}$, depends only on consumption place j once residence n is set. In the next steps, I trace consumers' decisions backwards and solve for individual's optimal workplace and consumption place.

Workplace choice. Having decided on residence n, worker i now chooses a workplace m that maximizes the worker's effective income. The worker i has complete information on the average wage per efficiency unit of labor (w_m) for all workplaces and the commuting costs between residence n and any potential workplace m. Additionally, the individual also observes the realized value of idiosyncratic productivity draws ($a_m(i)$) for all workplaces. I specify the workplace choice problem as

$$\max_{m|n} v_{nm}(i) = \frac{a_m(i) w_m}{\kappa_{nm}^W}.$$

Resident i who lives in cell n will choose to work at a given location m, if workplace m offers higher effective income ($v_{nm}(i)$) than any other alternative workplace m'. Therefore, the probability that location n's residents choose m as their workplace is given by

$$\lambda_{nm|n}^W = \prod_{m' \neq m} \text{Prob}\{v_{nm}(i) > v_{nm'}(i)\}.$$

The conditional commuting probability can be solved explicitly by integrating out the Fréchet distributions for productivity draws, and

$$\lambda_{nm|n}^W = \frac{T_m^W \left(\frac{w_m}{\kappa_{nm}^W}\right)^{\theta_W}}{\sum_{l \in N} T_l^W \left(\frac{w_l}{\kappa_{nl}^W}\right)^{\theta_W}}. \tag{3}$$

Equation 3 implies that workers favor workplaces that offer higher wages (larger T_m^W and w_m) with a lower commuting cost (κ_{nm}^W). The conditional commuting probability for workplace m is calculated by evaluating location m's attractiveness as a workplace, as captured in the numerator, against the attractiveness of all possible workplaces, as captured in the denominator.

I define residence n's workplace access as the ex ante expected level of workplace-driven utility ($\nu_{nm}(i)$) that the consumers can extract when applying their optimal workplace choices,

$$
\begin{aligned}
\mathbb{W}_n &= \mathbb{E}\left[\max\{\nu_{nm}(i)\}_{m\in N}|n\right] \\
&= \Gamma(\frac{\theta_W - 1}{\theta_W}) \cdot \left[\sum_{l\in N} T_l^W \left(\frac{w_l}{\kappa_{nl}^W}\right)^{\theta_W}\right]^{\frac{1}{\theta_W}},
\end{aligned} \tag{4}
$$

where $\Gamma(\cdot)$ is the Gamma function.

Commuting access $\mathbb{W}_n$ measures a residential location's ease of commuting to high-wage jobs. $\mathbb{W}_n$ also denotes the expected level of effective income for location n's residents, when workplace choice probabilities follow Equation 3.

Consumption place choice. Analogous to the workplace choices, the individual i will choose j as the location to consume services if the individual can extract more service-related utility from j compared to any other alternatives. When making consumption place choices, the individual observes service prices (P_{nS}), cost of travel for service trips (κ_{nj}^S), and individual-specific draw on the perceived quality of service ($d_j(i)$). The consumption place choice can be specified as

$$
\max_{j|n} \gamma_{nj}(i) = \left(\frac{d_j(i)}{P_{jS}\cdot\kappa_{nj}^S}\right)^{\alpha_S}.
$$

Then I can solve for the probability that a resident at n chooses j as consumption place as

$$
\lambda_{nj|n}^S = \frac{T_j^S\left(P_{jS}\cdot\kappa_{nj}^S\right)^{-\theta_S}}{\sum_{l\in N} T_l^S\left(P_{lS}\cdot\kappa_{nl}^S\right)^{-\theta_S}}. \tag{5}
$$

Equation 5 implies that consumers are more likely to consume services in places that offer higher-quality services (larger T_j^S) at a lower price (P_{jS}) and with a lower travel cost κ_{nj}^S.

I define a location's consumption access as the ex ante expectation over the service-related utility ($\gamma_{nj}(i)$) achieved with consumer's optimal choices on service locations.

$$
\begin{aligned}
\mathbb{S}_n &= \mathbb{E}\left[\max\{\gamma_{nj}(i)\}_{j\in N}|n\right] \\
&= \Gamma\left(\frac{\theta_S/\alpha_S - 1}{\theta_S/\alpha_S}\right)\cdot\left[\sum_{l\in N} T_l^S\left(P_{lS}\cdot\kappa_{nl}^S\right)^{-\theta_S}\right]^{\frac{\alpha_S}{\theta_S}},
\end{aligned}
\tag{6}
$$

Location n's consumption access ($\mathbb{S}_n$) measures the ease of travel from location n to inexpensive, high-quality services.

Residential choice problem. Now that I have solved consumers' subsequent decisions on workplace and consumption location, I trace the problem to the first step where consumers make residential decisions. Individual i, facing residential choices, do not yet observe the realization of idiosyncratic productivity and service-quality draws ($a_m(i)$ and $d_j(i)$), since they will only be realized in step (2). However, individuals do have information on the distribution of the idiosyncratic draws. Therefore, the individual at step (1) will not be certain on where the optimal workplace or consumption location will be but knows the probability associated with potential location choices. For example, individual i, before making residential choices, knows that if the individual chooses n as residence, the probability that m is the optimal workplace is as specified in Equation 3. With this probabilistic information, the individual will base the residential decision upon the ex ante expectation of maximum utility that can be derived from subsequent optimal choices, together with local price and amenity levels. The residential choice problem is specified as

$$
\begin{aligned}
\max_n \Omega_n(i) &= \frac{B_n b_n(i)}{P_{nT}^{\alpha_T} P_{nH}^{\alpha_H}}\cdot\mathbb{E}\left[\max\{\nu_{nm}(i)\}_{m\in N}|n\right]\cdot\mathbb{E}\left[\max\{\gamma_{nj}(i)\}_{j\in N}|n\right] \\
&= b_n(i)\frac{B_n}{P_{nT}^{\alpha_T} P_{nH}^{\alpha_H}}\mathbb{W}_n\mathbb{S}_n.
\end{aligned}
$$

I solve the residential probabilities as

$$\lambda_n^B = \frac{T_n^B \left(\frac{B_n}{P_{nT}^{\alpha_T} P_{nH}^{\alpha_H}} \mathbb{W}_n \mathbb{S}_n \right)^{\theta_B}}{\sum_{l \in N} T_l^B \left(\frac{B_l}{P_{lT}^{\alpha_T} P_{lH}^{\alpha_H}} \mathbb{W}_l \mathbb{S}_l \right)^{\theta_B}}. \tag{7}$$

Equation 7 shows that individuals are attracted to residential locations with desirable amenities (larger B_n and T_n^B), good commuting and consumption access ($\mathbb{W}_n$ and $\mathbb{S}_n$, respectively), and low prices for locally-consumed goods (P_{nT}, P_{nH}).

The ex ante expected utility that an individual can achieve by following the optimal location choices at every step is

$$\begin{aligned} \overline{U} &= \mathbb{E}[\max\{\Omega_n(i)\}_{n \in N}] \\ &= \Gamma\left(\frac{\theta_B - 1}{\theta_B}\right) \left[\sum_{l \in N} T_l^B \left(\frac{B_l}{P_{lT}^{\alpha_T} P_{lH}^{\alpha_H}} \mathbb{W}_l \mathbb{S}_l \right)^{\theta_B} \right]^{\frac{1}{\theta_B}}. \end{aligned} \tag{8}$$

The expected utility ($\overline{U}$) also measures overall consumer welfare.

4.2 Producer's problem

Non-tradable goods (services). Producers use a constant-return-to-scale production technology to produce non-tradable goods (services) from labor and productive floor space.

$$x_{mS} = A_m \left(\frac{\tilde{L}_m}{\beta} \right)^{\beta} \left(\frac{H_{mS}}{1-\beta} \right)^{1-\beta},$$

where x_{mS} is the total amount of service produced; A_m is the productivity of firms at location m; $\tilde{L}_m$ and H_{mS} denote the efficiency units of labor and floor space used as inputs in the production. β is the labor share in production, the key parameter that defines the technology.

Producers' first order conditions are given by

$$
\begin{aligned}
w_m &= P_{mS} A_m \beta \left(\frac{\tilde{L}_m}{\beta}\right)^{\beta-1} \left(\frac{H_{mS}}{1-\beta}\right)^{1-\beta}, \\
P_{mH} &= P_{mS} A_m (1-\beta) \left(\frac{\tilde{L}_m}{\beta}\right)^{\beta} \left(\frac{H_{mS}}{1-\beta}\right)^{-\beta}.
\end{aligned}
$$

This implies that the equilibrium prices and input demands should satisfy the following equations,

$$
P_{mS} = \frac{1}{A_m} w_m^{\beta} P_{mH}^{1-\beta}, \tag{9}
$$

$$
\frac{H_{mS}}{\tilde{L}_m} = \frac{1-\beta}{\beta} \left(\frac{P_{mS} A_m}{P_{mH}}\right)^{\frac{1}{\beta}}. \tag{10}
$$

Construction sector Construction firms use capital M_m and land K_m to produce floor space H_m with a constant-return-to-scale technology,

$$
H_m = M_m^{\mu} K_m^{1-\mu}.
$$

where μ is the capital share in floor space construction.

Perfect competition and cost minimization for the construction industry implies

$$
P_{mH} = \varphi_m H_m^{\frac{1-\mu}{\mu}},
$$

where $\varphi_m = \frac{1}{\mu} r K_m^{\frac{\mu-1}{\mu}}$ is a location-specific constant, and r is the cost of building capital common across locations in the city. The equation suggests an iso-elastic supply of floor space relative to its price.

4.3 Externalities

A location's productivity depends on its exogenous attributes (such as flatness, access to highways, etc.) and endogenous worker density,

$$A_m = \mathscr{A}_m \left(\frac{L_m}{K_m} \right)^{\eta_W}, \tag{11}$$

where $\mathscr{A}_n$ captures the exogenous components, and $\frac{L_m}{K_m}$ is the worker density. Parameter η_W governs the strength of agglomeration induced by production externality.

Analogously, a location's amenity level depends on its exogenous attributes (such as green space, access to good schools, etc.) and endogenous residential density,

$$B_n = \mathscr{B}_n \left(\frac{R_n}{K_n} \right)^{\eta_B}, \tag{12}$$

where $\mathscr{B}_n$ captures the exogenous components; R_n is the number of residents at location n that can be calculated from residential probability (λ_n^B) and the city's total population (Pop) as

$$R_n = \lambda_n^B Pop. \tag{13}$$

Parameter η_B governs the strength of residential externality. The externality induces agglomeration when η_B is positive and facilitates dispersion if η_B is negative.

4.4 Market Clearing

The market clearing conditions specify the set of equations where equilibrium prices and choice probabilities clear the local markets at each location.

With the choice probabilities, I can derive the demand of locally-consumed goods as follows.

$$x_{nT} = \frac{\alpha_T \mathbb{W}_n R_n}{P_{nT}},$$
$$H_{nB} = \frac{\alpha_H \mathbb{W}_n R_n}{P_{nH}},$$

Demands for services originates from both local and non-local consumers, which can be derived as

$$x_{mS} = \frac{1}{P_{mS}} \alpha_S \sum_n \lambda^S_{nm|n} \mathbb{W}_n R_n$$

In the market for non-tradable goods (services), I equate the supply and demand, and the market clearing condition can be characterized as

$$A_m \left(\frac{\tilde{L}_m}{\beta}\right)^{\beta} \left(\frac{H_{mS}}{1-\beta}\right)^{1-\beta} = \frac{1}{P_{mS}} \alpha_S \sum_n \lambda^S_{nm|n} \mathbb{W}_n R_n.$$

I define the total revenue received by location m's producers as E_m, and the market clearing condition in the service market implies

$$E_m = P_{mS} A_m \left(\frac{\tilde{L}_m}{\beta}\right)^{\beta} \left(\frac{H_{mS}}{1-\beta}\right)^{1-\beta} = \alpha_S \sum_n \lambda^S_{nm|n} \mathbb{W}_n R_n. \tag{14}$$

Assuming perfect competition in the markets and zero long-run profit for the firms, I can derive from producer's profit maximization problem the demand for labor and non-residential floor space as

$$\tilde{L}_m = \frac{\beta E_m}{w_m},$$
$$H_{mS} = \frac{(1-\beta) E_m}{P_{mH}}.$$

The supply of labor is equal to the sum of local labor supply and inflow of commuters,

$$L_m = \sum_n \lambda^W_{nm|n} R_n, \tag{15}$$

$$\tilde{L}_m = \sum_n \lambda^W_{nm|n} R_n \bar{a}_{nm}, \tag{16}$$

where $\bar{a}_{nm}$ is the average productivity of location n's residents who work at m, and

$$\bar{a}_{nm} = \Gamma(\theta^W)(T^W_m)^{\frac{1}{\theta^W}}$$

Finally in the housing market, I equate the supply of floor space with residential and production demands.

$$H_m = H_{mB} + H_{mS}.$$

4.5 Equilibrium

The equilibrium can be referenced by a set of price vectors ($\{P_{nH}, P_{nS}, P_{nT}\}$)[10], wage vector for an efficiency unit of labor ($\{w_m\}$), and choice probability vectors and matrices ($\{\lambda^B_n, \lambda^W_{nm|n}, \lambda^S_{nj|n}\}$), that clears the markets for labor, non-tradable goods, and floor space at every location. The set of exogenous parameters include the scale parameters ($\{T^B_n, T^W_m, T^S_j\}$) and dispersion parameters ($\theta_B, \theta_W, \theta_S$) defining the Fréchet distributions, travel costs ($\{\kappa^W_{nm}, \kappa^S_{nj}\}$), preference weights ($\alpha_T, \alpha_H, \alpha_S$), labor share in service production (β), capital share in floor space production (μ), parameters defining the strength of production and residential externalities (η_W, η_B), exogenous components in productivity and amenity ($\{\mathscr{A}_m, \mathscr{B}_n\}$), and the city's total population (Pop). Given the equilibrium vectors and matrices, all other equilibrium outcomes can be determined, such as labor inputs ($\{L_m, \tilde{L}_m\}$), housing inputs ($\{H_{mB}, H_{mS}\}$), service outputs ($\{x_{mS}\}$), access measures ($\{\mathbb{W}_n, \mathbb{S}_n\}$), level of welfare ($\overline{U}$), etc. The endogenous variables collectively solve the set of equa-

[10]In the following estimation, I take tradable goods as the numéraire and normalize its price (P_{nT}) to be 1.

tions summarized in Column (2) of Table 2. In the next section, I calibrate and estimate the parameters and retrieve unobserved residential amenities from equilibrium outcomes.

5 Quantitative Analysis and Results

5.1 Travel Costs

One key set of parameters I identify in the model are the travel costs ($\{\kappa_{nm}^{W}, \kappa_{nj}^{S}\}$). They dictate consumers' preference on workplace or consumption locations closer to their residence relative to faraway locations. Travel costs can be identified from the bilateral commuting and consumption probabilities specified in Equations 3 and 5.

To avoid complicated estimations on bilateral travel costs for each home-destination pair, I further parameterize the the model and impose an exponential relationship between travel costs and trip distances. Travel probabilities can then be transformed into log-linear gravity equations. For example, the commuting costs and probabilities are

$$\kappa_{nm}^{W} = \exp(-\phi^{W} \cdot \text{dist}_{nm}),$$
$$\log \lambda_{nm|n}^{W} = \Phi^{W} \text{dist}_{nm} + \psi_{m}^{W} + \xi_{n}^{W},$$

where dist_{nm} is the distance between locations n and m, ϕ^{W} is the semi-elasticity of commuting cost with respect to distance, Φ^{W} is the semi-elasticity of commuting probability with respect to distance, ψ_{m}^{W} and ξ_{n}^{W} are fixed effects capturing the location-specific characteristics, and

$$\begin{aligned}
\Phi^{W} &= \phi^{W} \theta_{W}, \\
\psi_{m}^{W} &= \log(T_{m}^{W} w_{m}^{\theta_{W}}), \\
\xi_{n}^{W} &= \log\left[\sum_{l \in N} T_{l}^{W} \left(\frac{w_{l}}{\kappa_{nl}^{W}}\right)^{\theta_{W}}\right].
\end{aligned}$$

The workplace fixed effect ψ_{m}^{W} signals workplace m's wage level, and residence fixed effect ξ_{n}^{W}

is associated with residence n's workplace access.

Finally, I add an idiosyncratic error term to capture other factors affecting travel probabilities apart from distance, such as availability of public transport, scenery, pleasure of the trip, etc. The gravity equations can then be estimated from observed travel probabilities using log-linear ordinary least squares (OLS) regressions or Poisson pseudo maximum likelihood (PPML) estimations with the following specifications:

$$\begin{aligned} \log \lambda^W_{nm|n} &= \Phi^W \text{dist}_{nm} + \psi^W_m + \xi^W_n + \varepsilon^W_{nm}, \\ \log \lambda^S_{nj|n} &= \Phi^S \text{dist}_{nj} + \psi^S_j + \xi^S_n + \varepsilon^S_{nj}. \end{aligned} \tag{17}$$

Table 3 reports the PPML estimates of the gravity coefficients (Φ) for various trip purposes. Each observation in the regression is a bilateral home-destination pair. Columns (1) to (4) reports estimates for all trips, commuting trips, consumption trips, and other trips, respectively. I define consumption trips to include dining and shopping trips. Overall, the estimates confirm a negative and statistically significant relationship between travel probabilities and trip distances for all trip purposes, with a semi-elasticity of -0.169 averaging over all trips documented in the survey. This suggests that destinations that are one-kilometer further away from a place of residence receive 16.9% less visits from the its residents on average. Specifically, the distance slope for bilateral consumption trips (-0.414) is much steeper relative to that of commuting trips (-0.100), consistent with estimates in the literature (Miyauchi et al., 2020; Hausman et al., 2021)[11]. The estimates reveal that consumers' perceived cost of travel is a few times higher when traveling for services, compared to the cost of commuting to work. The results accord with my observations from the surveys that consumption trips are on average shorter and more local compared to commuting trips.

In Figure A10, I present the result of a validation exercise for the gravity equations. I plot the observed and predicted values for a location's total number of workers (L_m) and total service revenue (E_m). The two variables are direct products of commuting and consumption probabilities as laid out in Equations 15 and 14. The prediction errors of the two variables plotted in the graph

[11] Nevertheless, both slopes are considerably steeper than those estimated for Tokyo in Miyauchi et al. (2020), consistent with the fact that Beijing's residents make shorter trips on average compared to Tokyo's residents.

are entirely driven by prediction errors in commuting and consumption probabilities. Correlation between the survey data and model predictions are 0.98 and 0.97, respectively, for the number of workers and service revenue. This suggest a very good fit of the gravity equation estimates in explaining the commuting and consumption patterns of the city.

5.2 Other Parameters

I start by calibrating the dispersion parameters for the Fréchet distributions as $\theta_B = \theta_W = \theta_S = 6$, following the estimated ranges in Ahlfeldt et al. (2015), Heblich et al. (2020), and Kreindler and Miyauchi (2021)[12]. Exploiting the spatial heterogeneity in access and amenities measures, I can identify and solve the location-specific scale parameters ($\{T_n^B, T_m^W, T_j^S\}$), as well as exogenous productivity ($\mathscr{A}_m$) and exogenous amenities ($\mathscr{B}_n$). In Section 6, I discuss a method that circumvents the estimations for constant location-specific parameters.

Next, the Cobb-Douglas preference weights ($\alpha_T, \alpha_H, \alpha_S$) are calibrated using observed consumers' expenditure shares from Beijing Municipal Bureau of Statistics, as implied by the optimal bundle in Equation 2. I set the expenditure share on tradable goods (α_T), residential housing (α_H), and non-tradable goods (α_S), to be 52%, 28% and 30% for 2010, respectively. The following years saw a large shift of consumers' demand from commodities to services, leading to a fifteen-percentage rise in expenditure share on services (to 45% in 2014) and a drop for tradable goods (to 24% in 2014). The survey also documents a modest uptick in consumer's spending on housing relative to non-housing sectors, partly owing to soaring housing prices. I use two sets of expenditure shares separately in the calibration for 2010 and 2014.

To define production technologies, I extrapolate from estimates in Bai and Qian (2010) and set the labor share in the service sector (β) as 0.60. I set the capital share in floor space production (μ) as 0.77 according to reports from China's Ministry of Land and Resources. I calibrate the externality parameters (η_W, η_B) from the literature (Rosenthal and Strange, 2004; Melo et al., 2009;

[12] Although none of the cited studies estimate the dispersion parameters for Beijing or China specifically, the difference in estimates across cities and regions are small. I do not estimate these parameters in this paper due to lack of precision or availability in data.

Ahlfeldt et al., 2015)[13].

5.3 Decomposition of Locations' Attractiveness

To estimate the role of environmental amenities in consumers' residential choices, I first retrieve unobserved residential amenities from locations' attractiveness as residential locations. I define a location's attractiveness from observed residential probability and housing price, combining Equations 8 and 7,

$$Attractiveness_n = (\lambda_n^B)^{\frac{1}{\theta_B}} P_{nH}^{\alpha_H} = \mathbb{W}_n \cdot \mathbb{S}_n \cdot \mathbb{B}_n. \tag{18}$$

where $\mathbb{W}_n$ and $\mathbb{S}_n$ measure location n's access to job and consumption locations, respectively. I define $\mathbb{B}_n$ as the residential amenity, capturing determinants of a location's attractiveness other than commuting and consumption access, and

$$\mathbb{B}_n = (T_n^B)^{\frac{1}{\theta_B}} \frac{B_n}{P_{nT}^{\alpha_T}} \cdot \frac{\Gamma(\frac{\theta_B - 1}{\theta_B})}{\overline{U}} = \frac{Attractiveness_n}{\mathbb{W}_n \mathbb{S}_n}. \tag{19}$$

The level of residential amenities ($\mathbb{B}_n$) differ across locations in the city only by the averages of Fréchet amenity shocks (T_n^B) and common amenity levels (B_n), since price of tradeable goods (P_{nT}), ex ante expected utility ($\overline{U}$), and dispersion of Fréchet shocks (θ_B) are the same for all locations. As such, the model is capable of evaluating the general equilibrium impacts from exogenous shocks in the provision of amenities, captured in B_n's, or those from a change in consumer preference on amenities, captured in T_n^B's.

Equation 18 implies that a location's attractiveness, characterized by observed equilibrium outcomes such as dense population (large λ_n^B) or expensive housing (large P_{nH}), can be attributed to desirable workplace access ($\mathbb{W}_n$), consumption access ($\mathbb{S}_n$), or a composite of other residential amenities ($\mathbb{B}_n$).

[13] There is a lack of consensus in the literature regarding the estimates for the externality parameters. I show in Section 6.2 that the welfare gains remain if I mute externalities in the model.

I plot in Figure A11 the overall attractiveness of each location as defined in Equation 18. Locations with highest attractiveness cluster within Beijing's 3rd ring road and align with locations with high residential densities and expensive housing.

I recover locations' workplace and consumption access using residence fixed effects from the gravity equation estimates,

$$\mathbb{W}_n^* = \Gamma(\frac{\theta_W - 1}{\theta_W}) \cdot \exp(\frac{1}{\theta_W}\xi_n^{W*}),$$
$$\mathbb{S}_n^* = \Gamma(\frac{\theta_S - 1}{\theta_S}) \cdot \exp(\frac{1}{\theta_S}\xi_n^{S*}).$$

where the superscript $*$ denotes estimated values; $\mathbb{W}_n^*$ and $\mathbb{S}_n^*$ are the estimated access measures; ξ_n^{W*} and ξ_n^{S*} are the estimated residence fixed effect for location n from Equation 17. Residential amenities can then be estimated using Equation 19.

In Figure 4, I present the estimates for workplace access, consumption access, and residential amenities for each location. The maps show a strong correlation between locations' commuting access ($\mathbb{W}$) and consumption access ($\mathbb{S}$). Individuals can enjoy greater commuting and consumption access if they reside in the central area of Beijing within the 4th ring road, where jobs, businesses, and public transportation lines concentrate. On the other hand, areas with desirable levels of residential amenity either concentrate in Beijing's core within the 2nd ring road or scatter around the suburban centers to the east and northwest.

In the next step, I undertake a variance decomposition practice to calculate the relative importance of each attraction component following the log-decomposition method implemented in Eaton et al. (2004) and Miyauchi et al. (2020). Specifically, I estimate the contributions of each component to the total variation in locations' attractiveness using a set of log-log OLS regressions, where I regress the log-transformed access or amenity measures individually on the log-transformed attractiveness measure.

$$
\begin{aligned}
\log \mathbb{W}_n &= v_W + k_W \log(Attractiveness_n) + u_W \\
\log \mathbb{S}_n &= v_S + k_S \log(Attractiveness_n) + u_S \\
\log \mathbb{B}_n &= v_B + k_B \log(Attractiveness_n) + u_B
\end{aligned}
\tag{20}
$$

By construction, the intercept terms in the three equations above sum up to zero ($v_W + v_S + v_B = 0$) and the slopes sum up to one ($k_W + k_S + k_B = 1$). Coefficient estimates on the slope terms (k_W, k_S, k_B) denote the proportion of variation in overall attractiveness that can be attributed each component. Appendix C explains the regression-based variance decomposition in detail.

Panel (d) in Figure 4 reports the estimated coefficients from Equation 20. The estimates suggest approximately half of a location's attractiveness to the population can be ascribed to its ease of commute to well-paid jobs, with another 21% to its accessibility of inexpensive high-quality services, and a remaining 30% to other residential amenities. The results are comparable with Miyauchi et al. (2020)'s findings for Tokyo where commuting and consumption access each accounts for 45% and 27% of the variation in attractiveness[14].

To further uncover the amenities cloaked under the composite term $\mathbb{B}$, I show in Table 5 the regression estimates of a location's residential amenity on its potential determinants, including its access to schools, hospitals, parks, and the location's air quality. Proximity indices for schools, hospitals, and parks are composed using inverse distance weighting, and air pollution levels are lagged by one year to avoid any endogeneity concern due to simultaneity. As the estimates show, in 2010, a location's proximity to schools and hospitals are strong predictors of its model-derived residential amenity: a one standard deviation change in the proximity indices for schools and hospitals corresponds to a 0.12 and 0.16 standard deviation change in the residential amenity on average. However, I find no significant link between the composite amenity term and environmental ameni-

[14] Miyauchi et al. (2020) construct estimates using data from Tokyo in 2019, where the expenditure share on the service sector is calibrated to be 66%, twice as large as Beijing's in 2010 (30%). My estimates for Beijing using data from 2014 is more comparable, where the expenditure share had increased to 45%, and commuting and consumption access each accounts for 44% and 28% of the variation in locations' attractiveness.

ties, implying their possible absence from the residents' decision process.

As a comparison, I re-calibrate the model and estimate the equilibrium outcomes using parameters and data from 2014. Column (2) in Table 5 presents the estimates. In contrast to earlier findings, the results document a significant positive correlation between a location's environmental qualities and its estimated level of residential amenity in 2014. Meanwhile, the coefficient estimates for non-environmental amenities (schools and hospitals) are similar to their 2010 counterparts. Specifically, a one standard deviation change in proximity to parks or in air pollution levels correlates to 0.14 and 0.19 standard deviation changes in the residential amenity, respectively. The estimates indicate that environmental amenities play a larger role in consumers' residential decisions in 2014 compared to 2010. The estimated results are robust to inclusion of additional district fixed effects as shown in Table A1.

There are several possible explanations for this change in consumers' preference structure. For one, rising income levels can boost consumers' demand on environmental amenities as they are often considered to be less affordable housing attributes or even a luxury (Martinez-Alier, 1995; Łaszkiewicz et al., 2019). Repeated incidences of extreme pollution events during the winter season in 2012 and 2013, coupled with the following government campaign for clean air, also contributed to consumers' increasing awareness on environmental challenges. In 2012, the introduction of pollution information disclosure programs in Beijing granted high-quality real-time pollution information streams directly to individuals, enabling potential residential sorting behaviors thereafter (Barwick et al., 2020). I show using an event study in Section 3 that the change in consumer preference during this period is not driven by rising income levels but rather the improvement in information availability and increasing consumer awareness on air pollution. This also explains the changes in consumer preference for parks. The information program implemented in 2012 not only increased the provision of air quality information but also changed people's awareness about the impact of clean air and being closer to parks on their health. When location-specific air pollution data is not available from the 27 monitoring stations in Beijing, individuals may also draw on a location's access to parks as a signal for clean air. Moreover, being closer to parks could itself capture the benefit from reduced air pollution on top of what the air pollution variable captures due to the coarseness of the air pollution data from remote sensing.

The absence of environmental amenities from consumers' decisions in 2010 and their introduction in 2014 invite interesting questions. If the preferences revealed from the 2014 survey are closer to consumers' true experience utility, and their decisions in 2010 are ill-informed, how large would the welfare loss be from these decisions? How would residential and job locations adjust, had residents in 2010 valued environmental amenities as they did in 2014? I explore these questions in detail through counterfactual analysis in the next section.

6 Counterfactuals

This section explains the exact-hat approach that solves the counterfactual equilibrium and discusses results from two counterfactual analyses. The first analysis focuses on consumers' enhanced preference towards environmental amenities and estimates its impact on equilibrium outcomes and the overall welfare. The second analysis estimates the general equilibrium elasticities of income and housing price from marginal air pollution shocks and derives consumers' willingness-to-accept for bearing polluted air.

6.1 Counterfactual Equilibrium

In this section, I apply the exact-hat algebra from the trade literature (Dekle et al., 2008) to the spatial general equilibrium model proposed in Section 4. Analogous to a comparative static analysis, the exact-hat approach totally differentiates the system of equations and express variables in the counterfactual using original equilibrium outcomes and the changes in between equilibria. This procedure produces a new system of equations that is computationally easy to solve as it eliminates location-specific parameters that are constant across equilibria. More importantly, the exact-hat approach relaxes identification assumptions on the model parameters and finesses convoluted estimations from inverting the whole model (Donaldson, 2016).

Appendix C explains the exact-hat algebra in detail. The system of equations established by the exact-hat method is summarized in Column (3) of Table 2, each derived from a corresponding equation in Column (2) that defines the equilibrium outcomes. In the following sections, I undertake two counterfactual analyses based on results derived from the exact-hat equation system.

6.2 Preference Change on Environmental Amenities

At the end of Section 5.3, I document a stronger emphasis on locations' environmental attributes when consumers selected residence in 2014 compared to 2010. If we are willing to assume that consumers in 2014 have refined their preference structure to incorporate the benefit and harms associated with environmental amenities but have not yet done so in 2010, it would imply that the equilibrium outcomes I observe in 2010's data are suboptimal. For instance, a typical consumer in 2010 would make a residential decision without internalizing the harm of air pollution and would thus experience polluted air. Collectively, this discrepancy between consumers' decision utility and experience utility will lead to a suboptimal distribution of residence across the city. Furthermore, the spatial distribution of employment and service production would also agglomerate towards misplaced residential centers to reduce consumers' travel costs. Through similar mechanisms embedded in the system of equations, the absence of environmental amenities will have extended consequences on all equilibrium outcomes that go beyond their direct impacts on residential locations.

In the following analysis, I estimate an alternative equilibrium using exact-hat algebra to explore the counterfactual scenario where consumers valued environmental amenities in 2010 as they did in 2014. I first calculate the counterfactual change in residential amenities by replacing 2010's coefficient estimates on environmental attributes (i.e. proximity to parks and air pollution level) in the first column in Table 5b with their 2014 counterparts in the second column[15]. This creates a shock in residential amenities that will drive the adjustments in other equilibrium outcomes. Using the original 2010 equilibrium as the initial guess (with $\widehat{z} = 1$ and $\Delta z = 0$ for any endogenous out-

[15]I scale the 2014 estimates down to comparable levels using CPI for tradable goods, as they are the anchor of price normalization.

come z), I update values of the endogenous variables iteratively until they reach a new equilibrium.

Counterfactual Equilibrium Outcomes. Figure 5 presents the equilibrium outcomes under the counterfactual scenario, measured by their changes from the original equilibrium levels. The figures each plot changes in equilibrium levels for residential amenities ($\widehat{\mathbb{B}}_n$), number of residents ($\widehat{R}_n$), number of workers ($\widehat{L}_m$), area of floor space ($\widehat{H}_n$), expected income of residents ($\widehat{\mathbb{W}}_n$), average wage of workers ($\widehat{w}_m$), and price of floor space ($\widehat{P}_{nH}$). Red cells denote negative changes compared to the initial equilibrium, such as fewer residents or workers, or decreases in wage, etc.; blue cells denote positive changes. For locations in the most polluted quartile (with an annual $PM_{2.5}$ concentration above 75 $\mu g/m^3$), the counterfactual analysis predicts an 18% drop in the number of residents, a 7% drop in the number of workers, a 3% increase in both residential income and workers' average wage, a 12% decrease in total area of floor space, and a 5% decrease in housing prices, at average levels.

Figure 5a, the first map of the set, shows the changes in residential amenities at the new equilibrium. They are nearly identical to the exogenous shock I initially introduce from the preference change, except that the equilibrium outcomes also adjust for residential externalities. The amenity shocks are negative for almost all locations as consumers' perception on pollution's harm overwhelms the benefits from green space. Particularly, the south and southeast sections of the city has poorer air quality and limited green space and therefore experience sizable drops in residential amenity levels as large as -30% to -50%.

Figures 5b and 5c plot the shift in population distributions. As expected, the estimates of the new equilibrium show a major relocation of residents from the city's polluted south to the northwest and the suburbs. Since residents favor closer workplaces and consumption places due to the cost of travel, job locations in the service sector also redeploy around new residential centers in response, as illustrated in Figure 5c. The changes in job density have a less distinct pattern compared to those for residential density due to the availability of commuting.

For additional labor market outcomes, I present in Figures 5e and 5f the changes in equilibrium income and wage. Changes in expected income directly reflect the monetary compensation associated with the lack of residential amenities. Unsurprisingly, I find a considerable increase in the residents' income in places where amenities are less satisfying. The estimates indicate that consumers' perceived cost of environmental damages can be as large as 4% of one's income in Beijing's most polluted areas. In Section 6.3, I leverage the trade-off between real income and pollution levels to estimate consumers' willingness to accept for air pollution and the damage curve of pollution. Wage levels, on the other hand, signal the relative strength in service production and labor supply. The equilibrium outcome shows a rise in workers' wage in the polluted city center, since workers in the new equilibrium would demand compensation to overcome higher commuting cost if they relocate to cleaner suburbs, or to offset the lack of amenities if they reside in polluted locations near workplace. Overall, the counterfactual change in consumers' amenity preference leads to higher costs for firms to acquire labor if the firms locate in the polluted areas of the city, even if environmental amenities do not directly affect production as I specify in the model. Recent studies suggest that poor air quality has a significant negative impact on worker productivity, though the scale of the impact varies with sector and region (Graff Zivin and Neidell, 2012; He et al., 2019; Chang et al., 2019). If I incorporate the productivity effects, the theoretical model would likely predict larger production relocation and wage adjustments.

In the housing market, the southern half of the city sees a substantial decline in both residential and production demand, leading to less occupied floor space (Figure 5d) and lower housing prices (Figure 5g) at equilibrium levels. I further partition the total change in floor space to changes in residential housing (Figure 6b) and non-residential housing (Figure 6c) which confirms the finding.

I repeat the event study analysis in Section 3, incorporating housing price adjustments from the counterfactual equilibrium. The estimates in Figure A14 show that if individuals had incorporated environmental amenities into their decisions prior to 2012, the capitalization of air pollution in the housing market will be of similar levels to that in the following years after the implementation of the pollution monitoring-and-disclosure program in Beijing.

Table A2 shows the semi-elasticity for each endogenous variables with respect to air pollution, the major driver of the amenity shock. I regress location-specific counterfactual changes on local air pollution levels in 2009, and estimate the semi-elasticities between the original and counterfactual equilibrium. The estimates are consistent with patterns observed in the previous plots. Specifically, I estimate a semi-elasticity of -0.003 for housing price, roughly on par with the estimated change in Figure A14.

Welfare Impacts. The adjustments in consumers' residential, workplace and consumption decisions entail notable welfare benefits. The overall welfare increase, which I calculate from $\widehat{\overline{U}}$ in Equation 1, amounts to 8.43% in the counterfactual equilibrium compared to the original. This is equivalent to the welfare change if I impose a 8.43% raise in income for all individuals, while holding all other variables at their unadjusted levels. For 2010, the welfare benefit translates to 2,450 Chinese *yuan* (or \$366 in 2010 dollars, \$440 in 2021 dollars[16]) per person. With a 20-million population, the total benefit for Beijing's residents adds up to 50 billion *yuan* in 2010, had they been internalizing environmental harms into their decisions. The counterfactual adjustments are mostly beneficial for residents residing in the polluted locations in 2010. Aggregating over different age and income groups, I find large welfare improvements for seniors and higher-income residents (Figures A12 and A13).

In Table 6, I explore five additional scenarios to identify the channels through which environmental amenities affect welfare. Scenario (0) corresponds to the full model I previously discussed, predicting a 8.43% increase in welfare.

In scenario (1), I mute the adjustments in the labor market ($\widehat{\mathbb{W}}_n$) by retaining each cell's original wage levels (w_m) and commuting probabilities ($\lambda^W_{nm|n}$). This incurs huge commuting costs directly to workers who have relocated away from their original workplace. As a result, scenario (1) predicts that almost all welfare benefits from residential and consumption adjustments will be offset if labor market outcomes are remain in situ.

In Scenario (2), I partial out the welfare benefit driven by service market adjustments ($\widehat{\mathbb{S}}_n$) by fixing service prices (P_{jS}) and consumption probabilities ($\lambda^S_{nj|n}$) at their original levels. The welfare

[16]In 2010, The average disposable income for Beijing's residents is 29,073 *yuan*. The exchange rate for USD/CNY is 6.7 in 2010. \$1 in 2010 is equal in buying power to \$1.20 in 2021 using chained CPI as the measurement.

contribution from the service market adjustments appears to be marginal compared to estimates for the labor market in Scenario (1), and the reasons are twofold. First, non-tradable goods and services accounts for less than one-third of consumers' expenditures, while their income depends entirely on labor market outcomes and commuting costs. As a result, consumers' welfare are more sensitive to changes in wage levels than those in service price. Secondly, the cost of consumption trips are much higher than that of commuting trips and an overwhelming majority of demand for services are met locally in both equilibria. This implies minor adjustments in conditional consumption probabilities between two equilibria and a small welfare change correspondingly.

Conversely, changes in housing price ($\widehat{P}_{nH}$) explain a sizable proportion of the welfare gain, despite housing's relatively small share (28%) in consumer expenditure. This is because housing is a local good that residents cannot substitute with non-local supplies (unless switching residence). More importantly, the price of floor space affects welfare through multiple pathways, including its direct implication with residential relocation and its complementarity with labor on the production side.

Scenarios (4) and (5) re-estimate two counterfactual equilibria where I set the strength of production externality (η_W) and residential externality (η_B) to zero, respectively. Both forces reshape the agglomeration of economic activities and affect the overall welfare at a moderate level.

In summary, if we assume consumers' utility are correctly specified in 2014, then the absence of environmental amenities in consumers' decision framework in 2010 would be associated with a substantial loss in welfare, due to suboptimal choices and market outcomes. In the counterfactual analysis, I apply consumers' enhanced preference on environmental amenities in 2014 onto the observed equilibrium in 2010 and find a 8.43% welfare improvement from consumers' decision adjustments. The welfare gain is equivalent to an income shock of 2,450 Chinese *yuan* (or $366) per person in 2010. The major channels explaining the welfare change are market forces in the labor and housing markets. The welfare estimates suggest large potential gains from government programs that, for example, facilitate air pollution information disclosure, or those that raises consumers' awareness on environmental amenities or the lack thereof.

6.3 Willingness to Accept on Air Pollution

In this section, I derive the cell-specific willingness to accept (WTA) or minimum compensation for individuals to bear additional pollution. I follow Rosen-Roback model of inter-urban sorting developed in Gao et al. (2021) and provide estimates with simulated equilibrium outcomes.

Gao et al. (2021) proposes that consumers' marginal willingness to pay (MWTP) for an amenity x is captured in the semi-elasticity of real income with respect to the amenity, if consumers reveal their true hedonic prices in their residential choices. MWTP can be calculated with the following equation.

$$MWTP_x = \frac{\partial \log(Income/P_H^{\alpha_H})}{\partial x} \times Income$$

where $Income$ denotes residential income, P_H denotes housing price, and α_H denotes housing share in consumer expenditure. The term $Income/P_H^{\alpha_H}$ measures residents' real income, i.e. housing price adjusted income.

To estimate the semi-elasticities, I compute 260 counterfactual exercises where I shock each inhabited cell with a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration, holding pollution levels in all other locations at their originally observed levels. I use the counterfactual equilibrium calculated in Section 6.2 as the baseline. From the simulated equilibrium outcomes, I can calculate the semi-elasticities for residents living in location n as $\frac{\widehat{\mathbb{W}}_n}{\widehat{P}_{nH}^{\alpha_H}}$.

Figure 7 plots the spatial distribution and kernel density of the estimates. I find the marginal willingness to accept being 25 *yuan* on average in compensation for a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration. The map shows substantial heterogeneity in the marginal willingness to accept across the city. Individuals residing in the cleaner northwest regions, for example, demand relatively higher compensation compared to those from polluted locations, since I estimate a downward sloping marginal damage curve with respect to pollution. Figure 8 plots the relationship between willingness to accept and pollution levels in an effort to retrieve the perceived marginal damage curve. Cells are grouped into 20 bins according to their pollution levels. The red line fits the within-bin averages, weighted by the residential population of the cells in each bin. The figure shows that residents whose home location enjoys the cleanest air in the city has a marginal willingness to accept as high as 50 *yuan*, three times greater than the estimates for those who live in the most polluted locations.

7 Conclusion

This paper studies the role of environmental amenities in shaping the distribution of economic activities in an urban system. I focus on consumers' increasing preference for environmental amenities in Beijing, a result of improved consumer awareness and information availability on locations' environmental qualities. Leveraging the spatial granularity of several rich and unique data sets, my analysis documents a large welfare improvement if consumers could incorporate environmental amenities into their decisions, compared to the scenario of not incorporating environmental amenities. The primary channels of impact are relocation of residents and across different neighborhoods within the city, as well as adjustments in local housing markets.

The findings from the study suggest large benefits from policies that facilitate information disclosure or raise public awareness on environmental amenities, such as pollution information monitoring-and-disclosure programs, news coverage on environmental risks, etc. As such, policy makers should commit to the availability, transparency, and accuracy of monitored data, as well as informing the public of the benefits and harms associated with environmental amenities or a lack thereof. Moreover, the analysis on Beijing highlights the significance of environmental amenities to both residential decisions and production activities in the city. As consumers' preference on environmental amenities grow, residents locations with better amenities would become more popular, and firms located in areas with less desirable amenities could face higher labor costs and lower demands due to costly commuting and consumption travels. City planning authorities should take both adjustments into account when designating land purposes or managing future urban development project. Finally, while my study is in the context of environmental amenities, the framework of the analysis could offer important guidance on urban planning in other settings such as site choices for new schools and hospitals, relocation of factories or government offices, etc. A comprehensive evaluation of such interventions, entailing not only their direct effects on one local market but also the extended impacts in the greater urban economy, is crucial for policy makers to make well-rounded decisions in order to reduce any inefficiencies in resource allocation.

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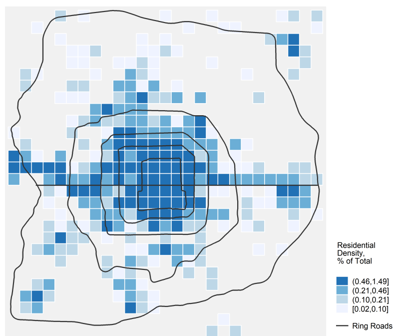
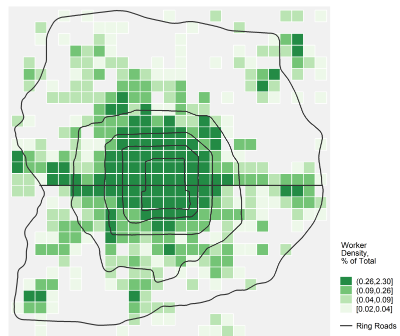
Figure 1: Spatial Patterns

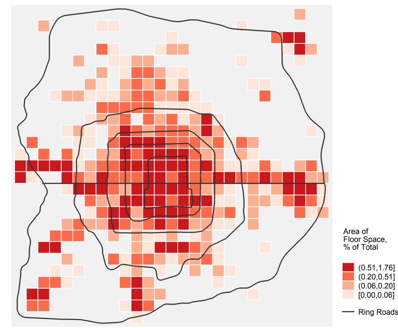
(a) Residential Density



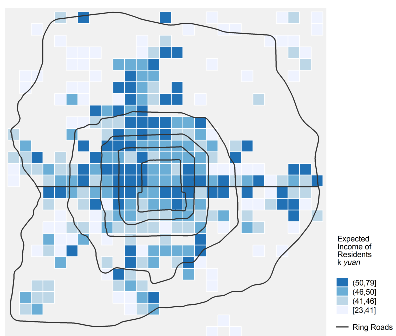
(b) Worker Density



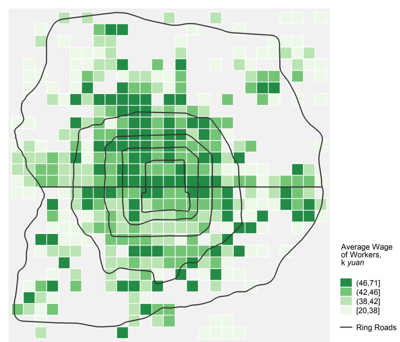
(c) Area of Floor Space



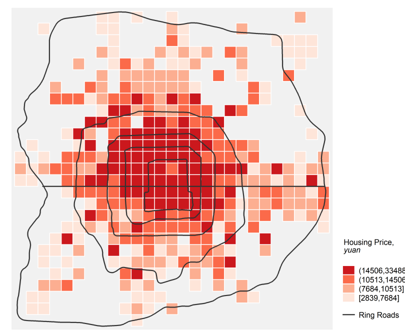
(d) Expected Income of Residents



(e) Average Wage of Workers



(f) Price of Floor Space



Notes:

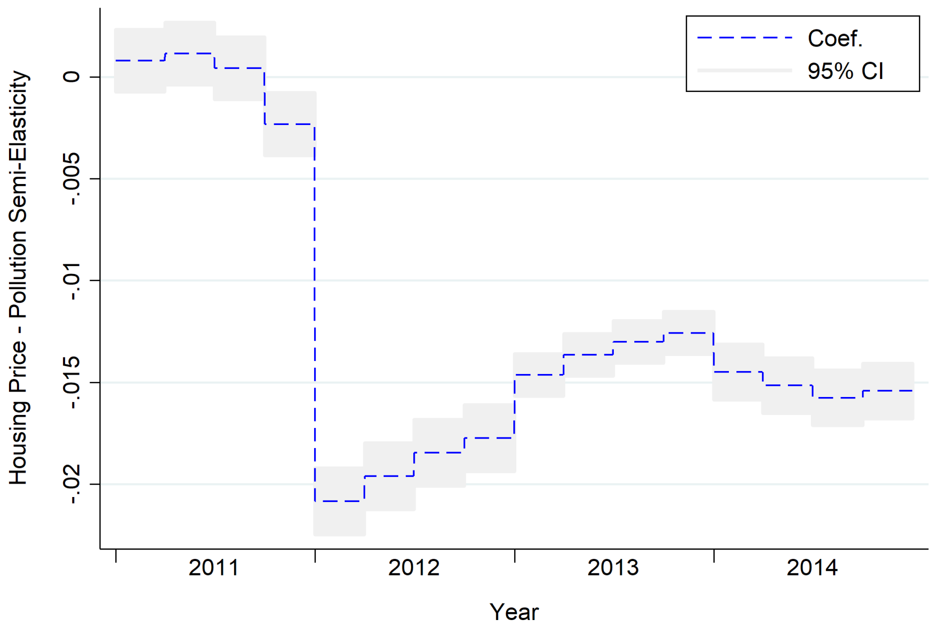
Figures (a)-(c) show the distribution of residents, workers and floor space at cell level, as percentages to the total number of residents, workers and total area of floor space in the area.

Figures (d)-(f) show the expected income of residents, average wage of workers and average price of floor space at each location. Figures showing income and wage exclude locations where the number of residents or workers is below 10, respectively.

The sample includes employed individuals (full-time and part-time) from Beijing Household Travel Survey (2010). The total number of sampled individuals is 49,454.

Deep color denotes higher density, income, or wage level.

Figure 2: Event Study: Semi-Elasticity of Housing Price w.r.t Air Pollution



Notes: The figure plots quarterly semi-elasticity of housing price with respect to air pollution for Beijing's housing transactions between 2011 and 2014. Controls include cell FEs, transaction year-month FEs, quadratic functions of unit and complex size, as well as other unit and complex characteristics (number of rooms, distance to nearest subway station at transaction date, school district, complex size and number of buildings).

Figure 3: Framework of the General Equilibrium Model

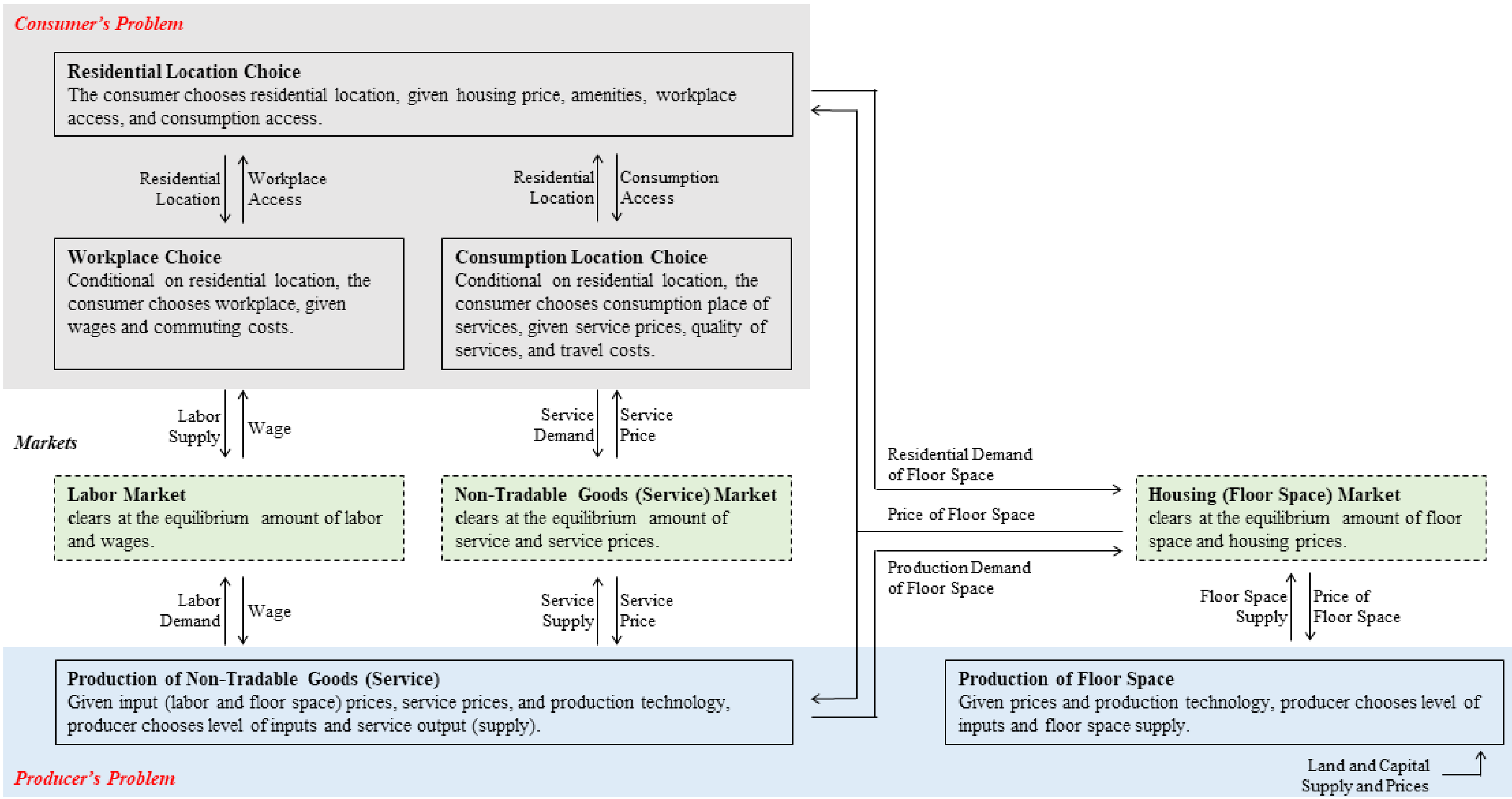
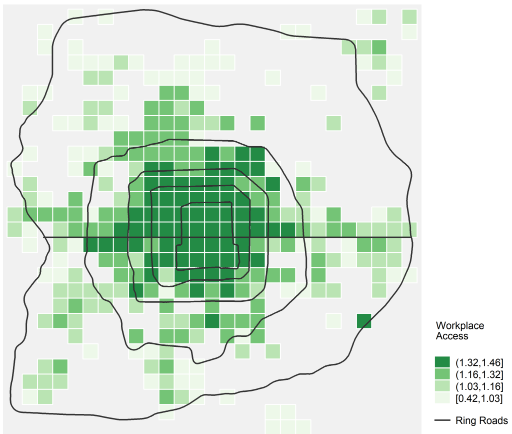
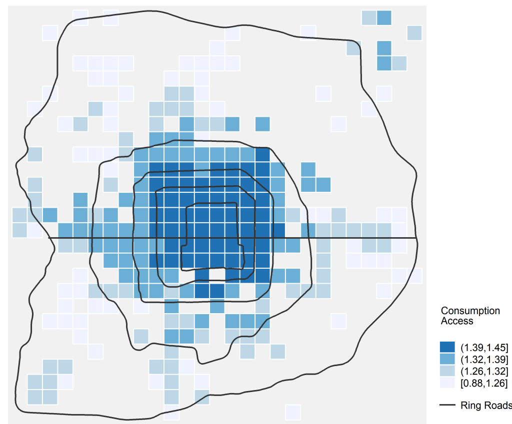


Figure 4: Decomposition of Locations' Attractiveness, 2010

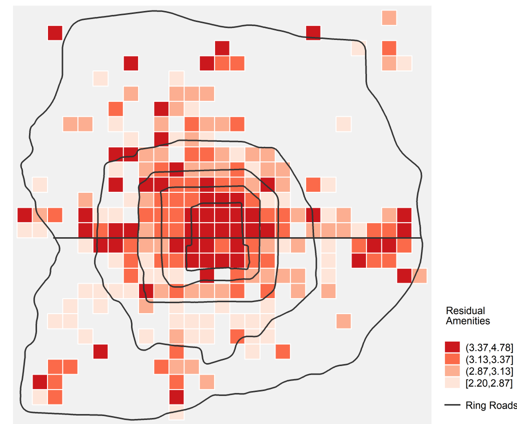
(a) Workplace Access, $\mathbb{W}_n$



(b) Consumption Access, $\mathbb{S}_n$



(c) Residential Amenities, $\mathbb{B}_n$



(d) Variance Decomposition

	log Workplace Access (1)	log Consumption Access (2)	log Residential Amenities (3)
log Attractiveness	0.49***	0.21***	0.30***
	(0.01)	(0.01)	(0.02)
R^2	0.83	0.64	0.43

Notes:

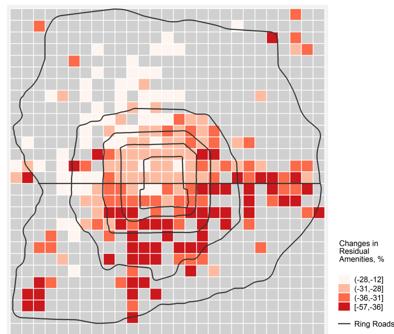
Figures plot the cell-level measure of (a) workplace access, (b) consumption access, and (c) residential amenities, derived from estimated results of the gravity equation. Residential amenities, workplace access, and consumption access cannot be estimated for home cells with insufficient data on work trips or consumption trips, or where price of floor space in unavailable.

Table (d) reports the estimation results of variance decomposition for each location's attractiveness from Equation 20. The dependent variables are log of (1) workplace access $\mathbb{W}$, (2) consumption access $\mathbb{S}$, and (3) residential amenities $\mathbb{B}$, respectively.

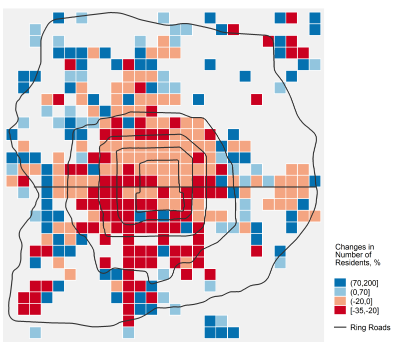
The independent variable is log of attractiveness for each location. I measure attractiveness with a composition of residential density and housing price, $(\lambda_n^B)^{\frac{1}{\theta_B}} P_{nH}^{\alpha_H}$.

Figure 5: Counterfactual Equilibrium, % Changes Relative to Original Eq'm

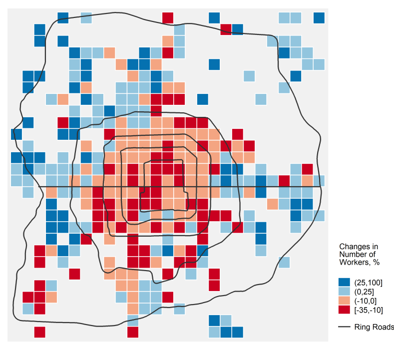
(a) Residential Amenities



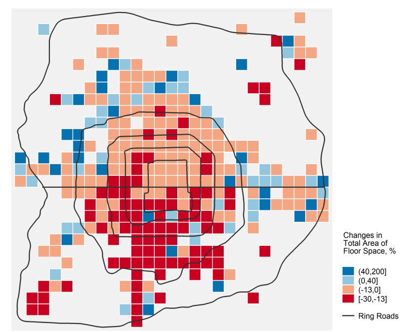
(b) Number of Residents



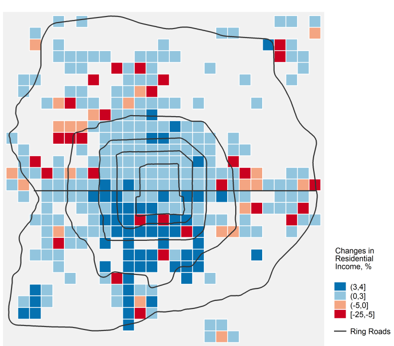
(c) Number of Workers



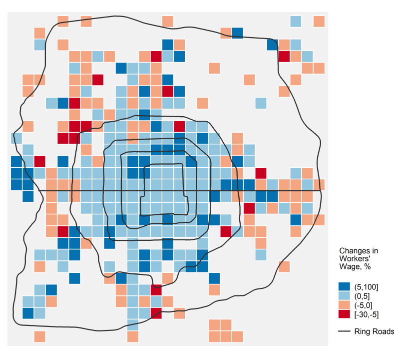
(d) Area of Floor Space



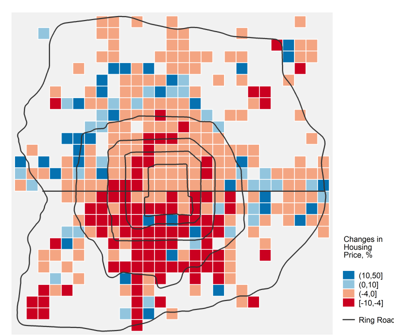
(e) Expected Income of Residents



(f) Average Wage of Workers



(g) Price of Floor Space



Notes:

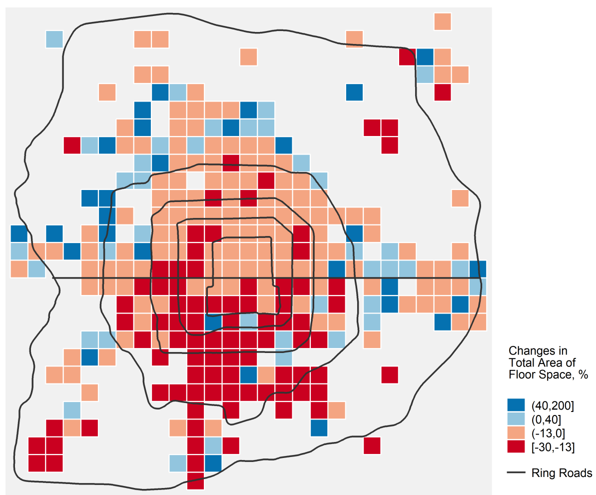
Figure (a) plots the counterfactual changes to residential amenities introduced in the counterfactual scenario where residents in 2010 would value environmental amenities as they did in 2014.

Figures (b) - (g) plot for each location the percentage changes of variables at the new equilibrium level relative to the original equilibrium observed in 2010.

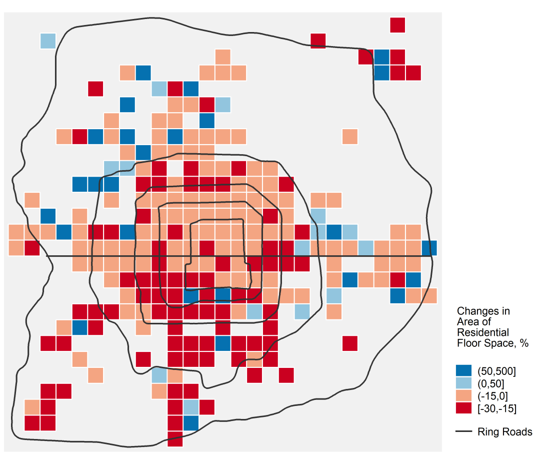
Red denotes negative changes (e.g. fewer residents or workers, decrease in wage or income) and blue positive changes.

Figure 6: Changes in Area of Floor Space, % Changes Relative to Original Eq'm

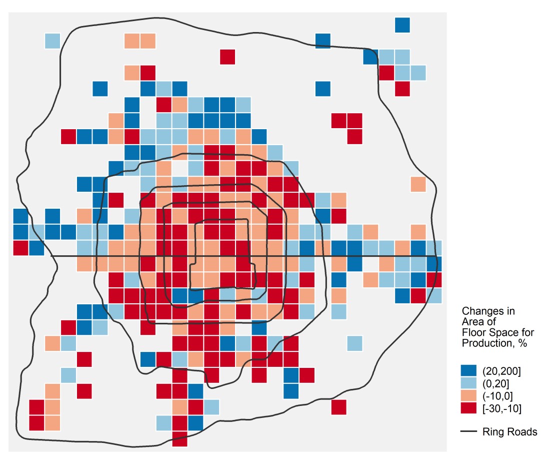
(a) Total Area of Floor Space



(b) Residential Use



(c) Production Use



Notes:

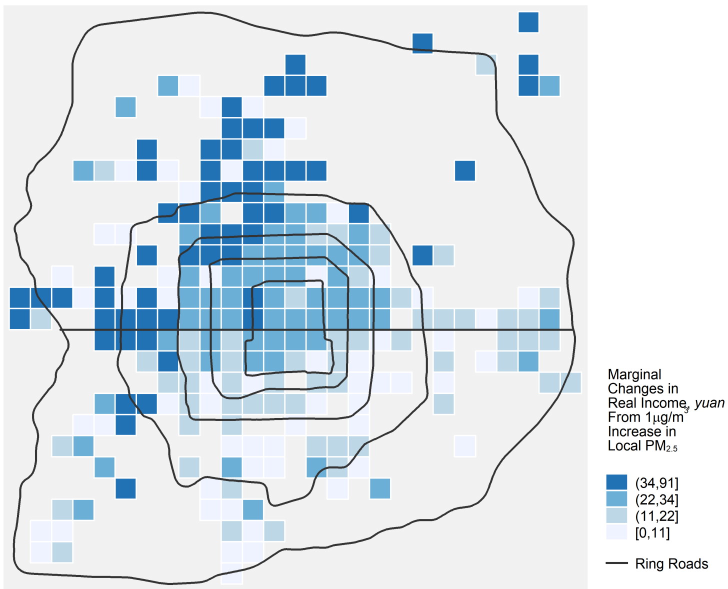
Figure (a) plots the counterfactual changes to the total area of floor space for each location at the new equilibrium level relative to the original equilibrium observed in 2010.

Figures (b) and (c) plots the changes in floor space for residential use and production use, respectively.

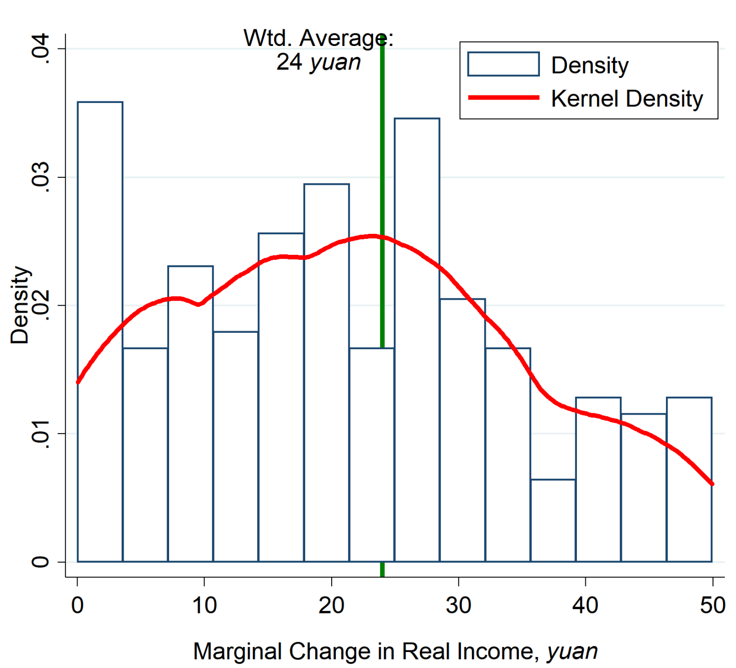
Red denotes decreases in the area floor space and blue increases.

Figure 7: Real Income Elasticity to Pollution Shock

(a) Spatial Distribution

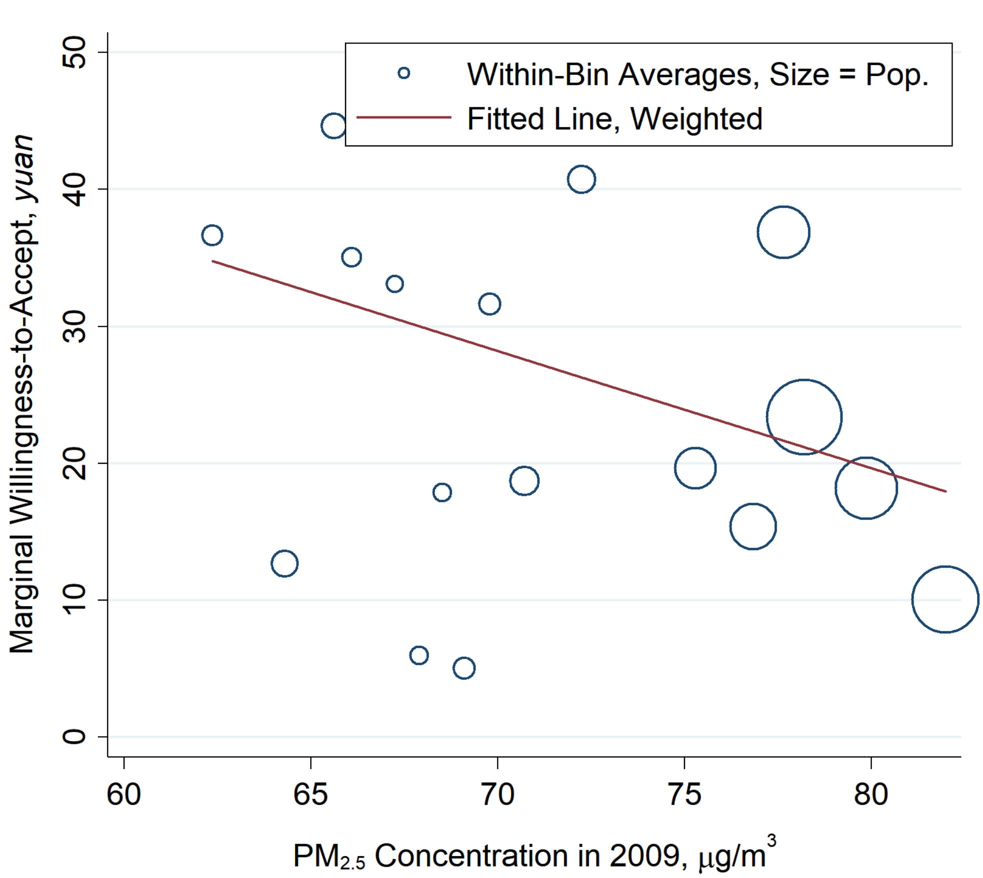


(b) Kernal Density



Notes: Figure (a) plots the spatial distribution of marginal willingness to accept for a 1 μg/m^3 pollution increase. Figure (b) plots the kernel density.

Figure 8: Marginal Willingness to Accept v. Air Pollution



Notes:

This figure plots the relationship between consumers' willingness-to-accept (WTA) to compensate for a 1 μg/m^3 increase in annual average $PM_{2.5}$ concentration level and their home locations' pollution levels in 2009.

Marginal willingness to accept for each location is the product of observed average income and the real income elasticity to pollution which I derive from the counterfactual analysis.

Residential locations are grouped into 20 bins by their pollution levels in 2009. The center of each circle denotes the within-group weighted averages of WTA and pollution, with the weights being the number of residents for each location. The size of the circle denotes the total number of residents for the locations in each bin. The red line is the weighted linear fit from the within-group averages.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Individual level					
Income, *yuan*	44,063.76	27,589.76	6,250	400,000.00	48,338
Male	0.54	-	-	1.00	48,338
Location (cell) level					
Number of residents	142.22	150.30	1.00	721.00	340
Number of workers	85.49	516.86	1.00	12,783.00	647
Avg. income of residents	42,010.14	10,495.33	16,666.67	100,000.00	340
Avg. wage of workers	40,664.76	14,621.15	12,500.00	275,000.00	647
Housing price	11,357.54	4,837.66	2,839.00	33,488.00	356
Proximity indices for					
Schools	708.91	200.95	315.65	1,301.57	756
Hospitals	6.78	16.94	1.66	285.06	756
Parks	6.89	27.09	1.41	507.70	756
$PM_{2.5}$ concentration, $\mu g/m^3$	69.82	7.92	31.80	84.95	756

Notes:

The sample includes all employed individuals in Beijing Household Travel Survey (2010). The unit for income, wage, and housing price is Chinese *yuan*.

Table 2: System of Equations and Exact-hat Algebra

Variable description	Variable, z	Counterfactual changes, $\widehat{z}$
Commuting probability	$\lambda^W_{nm\|n} = \frac{T^W_m \left(\frac{w_m}{\kappa^W_{nm}}\right)^{\theta_W}}{\sum_{l\in N} T^W_l \left(\frac{w_l}{\kappa^W_{nl}}\right)^{\theta_W}}.$	$\widehat{\lambda}^W_{nm\|n} = \frac{\left(\widehat{w}_m/\widehat{\kappa}^W_{nm}\right)^{\theta_W}}{\sum_{l\in N}\left(\widehat{w}_l/\widehat{\kappa}^W_{nl}\right)^{\theta_W}\lambda^W_{nl\|n}}$
Consumption probability	$\lambda^S_{nj\|n} = \frac{T^S_j\left(P_{jS}\cdot\kappa^S_{nj}\right)^{-\theta_S}}{\sum_{l\in N} T^S_l\left(P_{lS}\cdot\kappa^S_{nl}\right)^{-\theta_S}}$	$\widehat{\lambda}^S_{nj\|n} = \frac{\left(\widehat{P}_{jS}\widehat{\kappa}^S_{nj}\right)^{-\theta_S}}{\sum_{l\in N}\left(\widehat{P}_{lS}\widehat{\kappa}^S_{nl}\right)^{-\theta_S}\lambda^S_{nl\|n}}$
Residential probability	$\lambda^B_n = \frac{T^B_n\left(\frac{B_n}{P_{nT}^{\alpha_T}P_{nH}^{\alpha_H}}\mathbb{W}_n\mathbb{S}_n\right)^{\theta_B}}{\sum_{l\in N} T^B_l\left(\frac{B_l}{P_{lT}^{\alpha_T}P_{lH}^{\alpha_H}}\mathbb{W}_l\mathbb{S}_l\right)^{\theta_B}}$	$\widehat{\lambda}^B_n = \frac{\left(\widehat{B}_n\widehat{\mathbb{W}}_n\widehat{\mathbb{S}}_n/\widehat{P}_{nH}^{\alpha_H}\right)^{\theta_B}}{\sum_{l\in N}\left(\widehat{B}_l\widehat{\mathbb{W}}_l\widehat{\mathbb{S}}_l/\widehat{P}_{lH}^{\alpha_H}\right)^{\theta_B}\lambda^B_l}$
Commuting access	$\mathbb{W}_n = \Gamma(\frac{\theta_W-1}{\theta_W})\cdot\left[\sum_{l\in N} T^W_l\left(\frac{w_l}{\kappa^W_{nl}}\right)^{\theta_W}\right]^{\frac{1}{\theta_W}}$	$\widehat{\mathbb{W}}_n = \left[\left(\widehat{w}_n/\widehat{\kappa}^W_{nn}\right)^{\theta_W}/\widehat{\lambda}^W_{nn\|n}\right]^{\frac{1}{\theta_W}}$
Consumption access	$\mathbb{S}_n = \Gamma\left(\frac{\theta_S/\alpha_S-1}{\theta_S/\alpha_S}\right)\cdot\left[\sum_{l\in N} T^S_l\left(P_{lS}\cdot\kappa^S_{nl}\right)^{-\theta_S}\right]^{\frac{\alpha_S}{\theta_S}}$	$\widehat{\mathbb{S}}_n = \left[\left(\widehat{P}_{nS}\widehat{\kappa}^S_{nn}\right)^{-\theta_S}/\widehat{\lambda}^S_{nn\|n}\right]^{\frac{\alpha_S}{\theta_S}}$
Expected utility	$\overline{U} = \Gamma\left(\frac{\theta_B-1}{\theta_B}\right)\left[\sum_{l\in N} T^B_l\left(\frac{B_l}{P_{lT}^{\alpha_T}P_{lH}^{\alpha_H}}\mathbb{W}_l\mathbb{S}_l\right)^{\theta_B}\right]^{\frac{1}{\theta_B}}$	$\widehat{\overline{U}} = \left[\sum_{l\in N}\left(\widehat{\mathbb{B}}_l\widehat{\mathbb{W}}_l\widehat{\mathbb{S}}_l/\widehat{P}_{lH}^{\alpha_H}\right)^{\theta_B}\lambda^B_l\right]^{\frac{1}{\theta_B}}$
Price of services	$P_{mS} = \frac{E_m}{A_m\left(\frac{L_m}{\beta}\right)^{\beta}\left(\frac{H_{mS}}{1-\beta}\right)^{1-\beta}}$	$\widehat{P}_{mS} = \frac{\widehat{E}_m}{\widehat{A}_m\widehat{L}_m^{\beta}\widehat{H}_{mS}^{1-\beta}}$
Price of floor space	$P_{mH} = \varphi_m H_m^{\frac{1-\mu}{\mu}}$	$\widehat{P}_{mH} = \widehat{H}_m^{\frac{1-\mu}{\mu}}$
Wage	$w_m = \left(P_{mS}A_m/P_{mH}^{1-\beta}\right)^{\frac{1}{\beta}}$	$\widehat{w}_m = \left(\widehat{P}_{mS}\widehat{A}_m/\widehat{P}_{mH}^{1-\beta}\right)^{\frac{1}{\beta}}$
Floor space	$H_m = H_{mB} + H_{mS}$	$\widehat{H}_m = \frac{\widehat{H}_{mS}H_{mS}+\widehat{H}_{mB}H_{mB}}{H_{mS}+H_{mB}}$
Production floor space	$H_{mS} = \frac{(1-\beta)E_m}{P_{mH}}$	$\widehat{H_{mS}} = \frac{\widehat{E}_m}{\widehat{P}_{mH}}$
Residential floor space	$H_{nB} = \frac{\alpha_H\mathbb{W}_nR_n}{P_{nH}}$	$\widehat{H_{nB}} = \frac{\widehat{\mathbb{W}}_n\widehat{R}_n}{\widehat{P}_{nH}}$
Service expenditure	$E_m = \alpha_S\sum_n\lambda^S_{nm\|n}\mathbb{W}_nR_n$	$\widehat{E}_m = \frac{E'_m}{E_m} = \frac{\sum_n\lambda'^S_{nm\|n}\mathbb{W}'_nR'_n}{\sum_n\lambda^S_{nm\|n}\mathbb{W}_nR_n}$
Efficiency units of labor	$\tilde{L}_m = \frac{\beta E_m}{w_m}$	$\widehat{\tilde{L}}_m = \frac{\widehat{E}_m}{\widehat{w}_m}$
Number of workers	$L_m = \sum_n\lambda^W_{nm\|n}R_n$	$\widehat{L}_m = \frac{L'_m}{L_m} = \frac{\sum_n\lambda'^W_{nm\|n}R'_n}{\sum_n\lambda^W_{nm\|n}R_n}$
Number of residents	$R_n = \lambda^B_n Pop$	$\widehat{R}_n = \widehat{\lambda}^B_n$
Productivity	$A_m = \mathscr{A}_m L_m^{\eta_W}$	$\widehat{A}_m = \widehat{L}_m^{\eta_W}$
Residential amenity	$B_n = \mathscr{B}_n R_n^{\eta_B}$	$\widehat{B}_n = \widehat{R}_n^{\eta_B}$

Notes: I take tradable goods as the numéraire and normalize its price (P_{nT}) to be 1.

Table 3: Estimation Results for Gravity Equations

	Conditional Travel Probability, $\lambda_{ni\|n}$			
	All Trips	Work	Consumption	Other
	(1)	(2)	(3)	(4)
Distance	-0.169***	-0.100***	-0.414***	-0.209***
	(0.008)	(0.006)	(0.019)	(0.013)
N	15,002	14,975	13,886	14,849

Notes:

This table reports the PPML estimates of the gravity coefficients in Equation 17 for (1) all trips, (2) work trips, (3) consumption (shopping and dining) trips, and (4) other trips.

Each observation is a pair of origin-destination cells. The dependent variable $\lambda_{ni|n}$ is the conditional probability of cell n's residents visiting cell i for a certain type of trip. The independent variable is the distance between the centroids for a origin-destination cell pair. Coefficient estimates are semi-elasticities of travel probability with respect to trip distances.

Table 4: Calibrated and Estimated Structural Parameters

Description	Parameter	Value
Dispersion of Fréchet shocks	θ_W, θ_S, θ_B	6
Consumer expenditure share on		
Tradable goods	α^T	42%
Residential housing	α^H	28%
Non-tradable goods	α^S	30%
Semi-elasticities of travel probability w.r.t. distance for		
Commuting trips	Φ_W	-0.10
Consumption trips	Φ_S	-0.41
Production technology		
Labor share in service production	β	0.60
Capital share in floor space production	μ	0.77
Production externality	η_W	3%
Residential externality	η_B	-1%

Notes:

Consumer expenditure shares are calibrated from consumer surveys conducted by Beijing Municipal Bureau of Statistics. In 2014, consumer expenditure shares on tradable goods, housing, and non-tradable goods are 24%, 31%, and 45%, respectively.

Semi-elasticities of travel with respect to trip distances are PPML estimates in Table 3, calculated using bilateral travel data from Beijing Household Travel Survey (2010).

Factor shares in service production are extrapolated from Bai and Qian (2010).

Factor shares in floor space production are calibrated from Ministry of Land and Resources, PRC (2009).

Table 5: Decomposition of Residential Amenity $\mathbb{B}$

(a) Standardized Beta Coefficient Estimates

	Residential amenity $\mathbb{B}$	
	(1)	(2)
	2010	2014
Proximity index for		
Schools	0.11*	0.14**
	(0.07)	(0.06)
Hospitals	0.16***	0.16***
	(0.07)	(0.06)
Parks	-0.08	0.18***
	(0.07)	(0.06)
Air pollution $_{year-1}$	-0.04	-0.24***
	(0.07)	(0.06)
N	238	237
R^2	0.05	0.13

(b) OLS Coefficient Estimates

	Residential amenity $\mathbb{B}$	
	(1)	(2)
	2010	2014
Proximity index for		
Schools	0.21**	0.32**
	(0.11)	(0.16)
Hospitals	0.16***	0.25***
	(0.06)	(0.09)
Parks	-0.02	0.06**
	(0.02)	(0.03)
Air pollution $_{year-1}$	0.37	-1.96***
	(0.58)	(0.65)
N	234	236
R^2	0.05	0.09

Notes:

Panel (a) reports estimates of standardized coefficients, where all variables in regression are standardized to zero mean and unit variance. Panel (b) reports OLS coefficient estimates.

The dependent variable measures residential amenities $\mathbb{B}$ for year 2010 (Column 1) and 2014 (Column 2), respectively. Residential amenity is calculated as a location's attractiveness net of its commuting and consumption accessibility,

$$\mathbb{B}_n = \frac{(\lambda_n^B)^{\frac{1}{\theta_B}} P_{nH}^{\alpha_H}}{\mathbb{W}_n \mathbb{S}_n}.$$

Proximity indices of amenity J for cell n are constructed as

$$index_n^J = \sum_{j \in J} \frac{1}{d_{nj}} x_j,$$

Table 6: Channels of Welfare Impacts

	Scenarios	% Change in Welfare
(0)	Full model	8.43%
(1)	Without labor market adjustment	0.80%
(2)	Without service market adjustment	8.08%
(3)	Without housing market adjustment	2.87%
(4)	Without production externality	5.36%
(5)	Without residential congestion	5.03%

Notes:

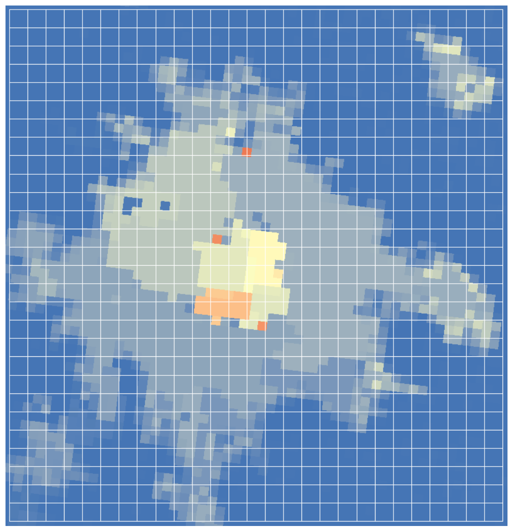
Scenario (0) corresponds to the counterfactual equilibrium estimated with the full model.
In Scenarios (1) to (3), I shutdown adjustment in the labor, service, and housing market, respectively.
Scenarios (4) mutes the production externality, and scenario (5) mutes the residential externality (congestion).
Percentage change in welfare is calculated as $\widehat{\overline{U}} - 1$.

Appendices

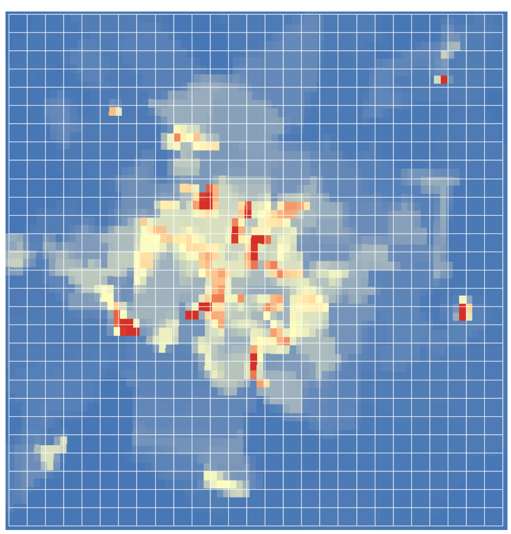
A Descriptive Data Pattern

Figure A1: Estimated Population Density

(a) CAS

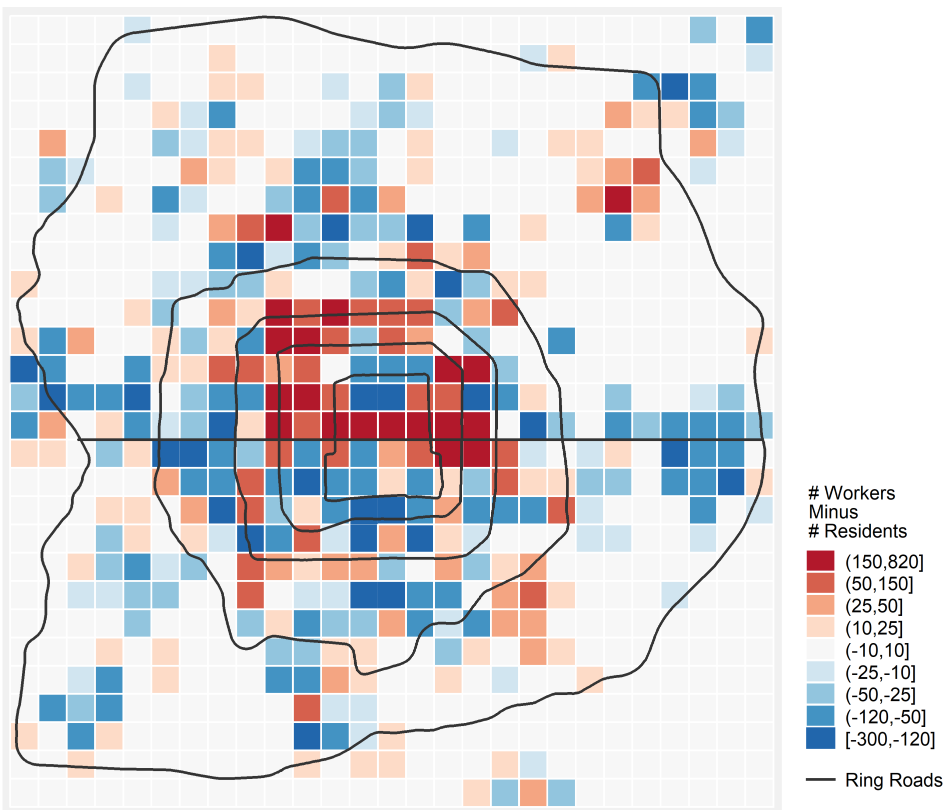


(b) NASA



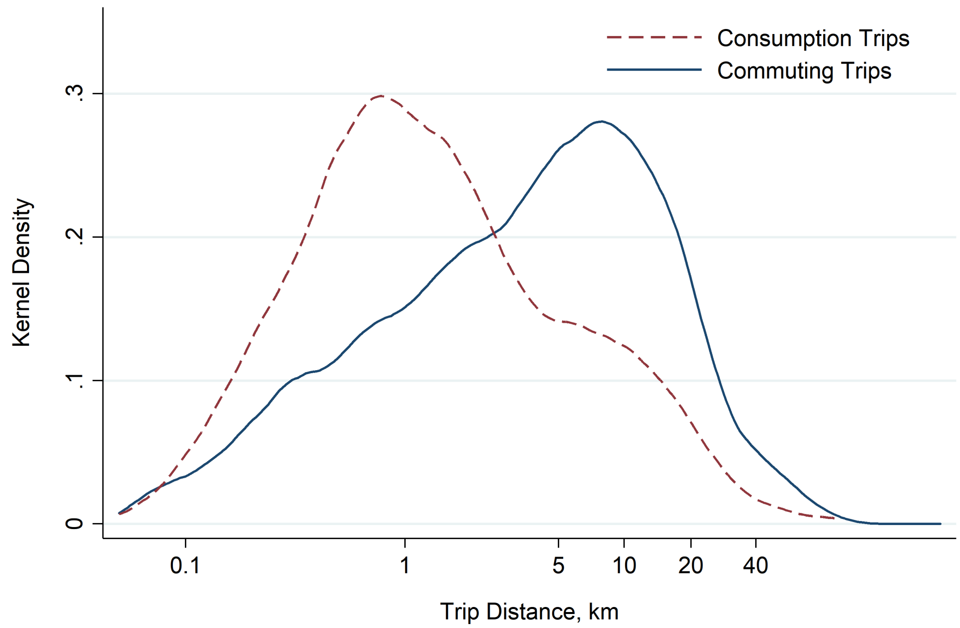
Notes: The figures show the estimated population density for the study area from (a) Chinese Academy of Science (CAS) and (b) NASA, based on census data and land use.

Figure A2: Commuting Flows, 2010



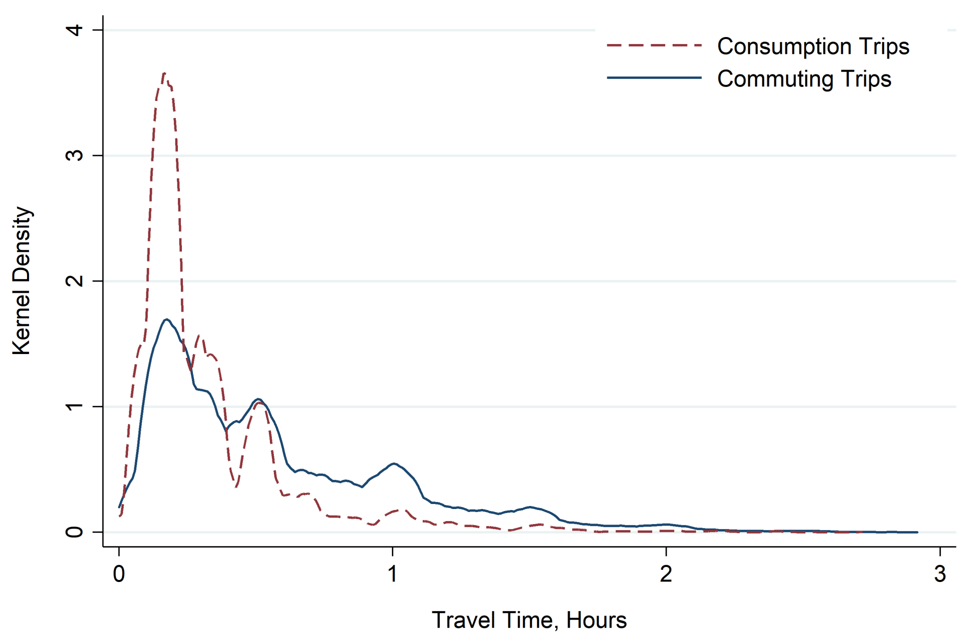
Notes: The figure shows the commuting flow in Beijing in 2010. Cells in red denote locations with more jobs than residents, with a net inflow of commuting workers; cells in blue denote locations with more residents than jobs, with a net outflow of commuting workers.

Figure A3: Travel Distance of Commuting and Consumption Trips, 2010



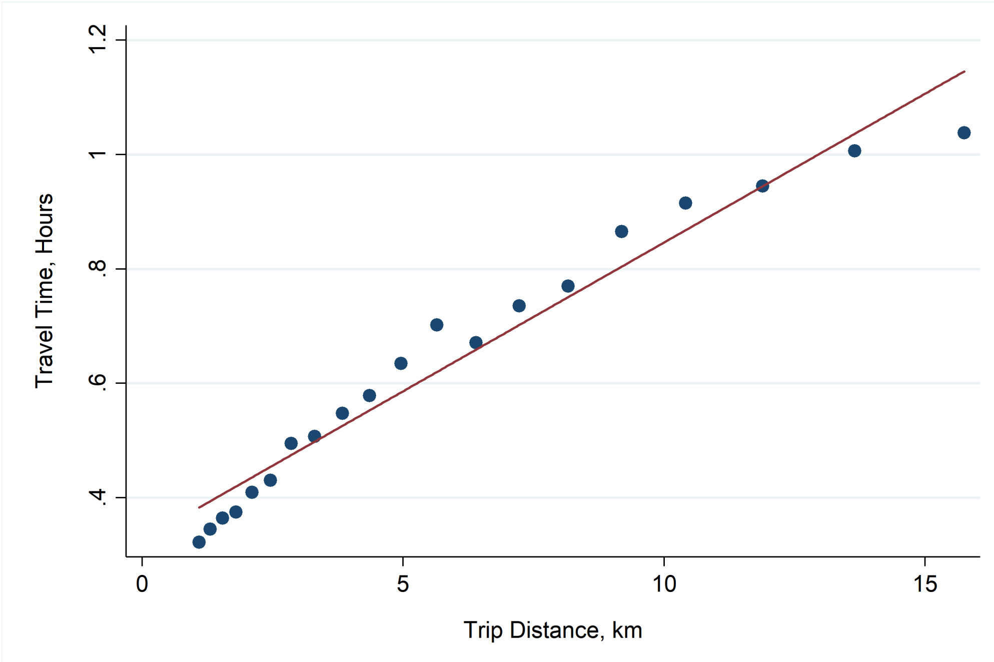
Notes: The figure shows the kernel density of travel distance for commuting trips (blue line) and consumption trips (red line).

Figure A4: Travel Time of Commuting and Consumption Trips, 2010



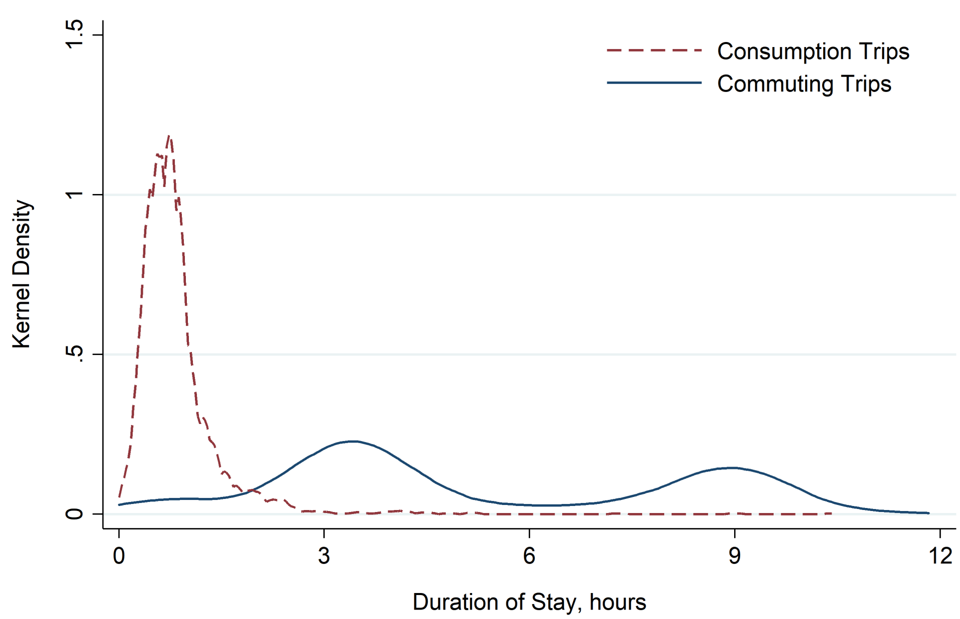
Notes: The figure shows the kernel density of travel time for commuting trips (blue line) and consumption trips (red line).

Figure A5: Travel Time vs. Trip Distance, 2010



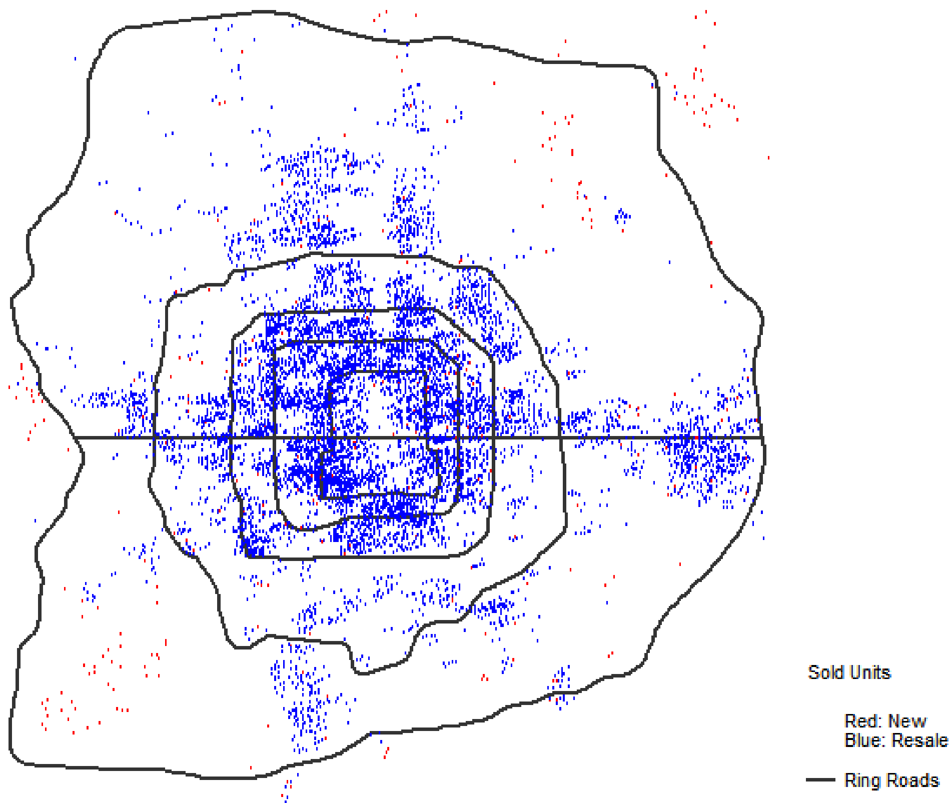
Notes: The figure shows the relationship between travel time (y-axis) and trip distance (x-axis). Sample excludes 10% trips with longest trip distances. Trips are grouped into 20 bins according to trip distanced.

Figure A6: Duration of Stay for Commuting and Consumption Trips, 2010



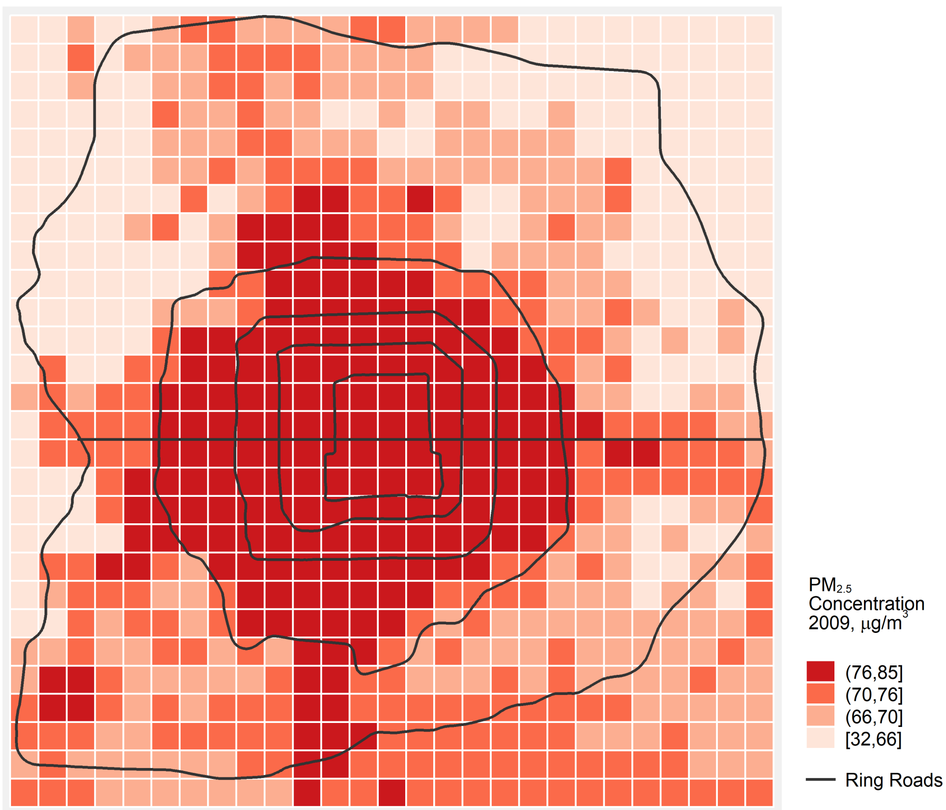
Notes: The figure shows the kernel density of stay duration for commuting trips (blue line) and consumption trips (red line).

Figure A7: Housing Unit Locations



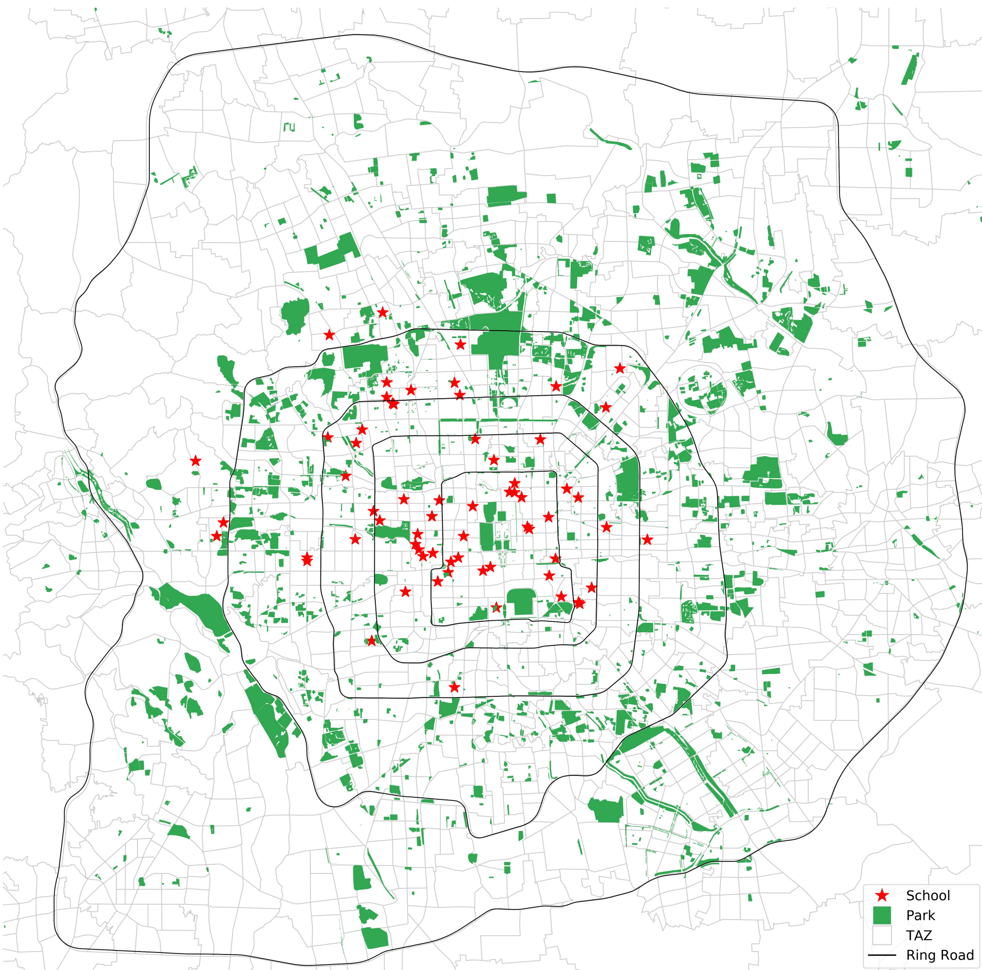
Notes: The figure shows locations of housing units in the housing transaction sample collected from two major real estate firms in Beijing. Red dots denotes locations of new housing units; blue dots denotes resales.

Figure A8: $PM_{2.5}$ Concentration, 2009



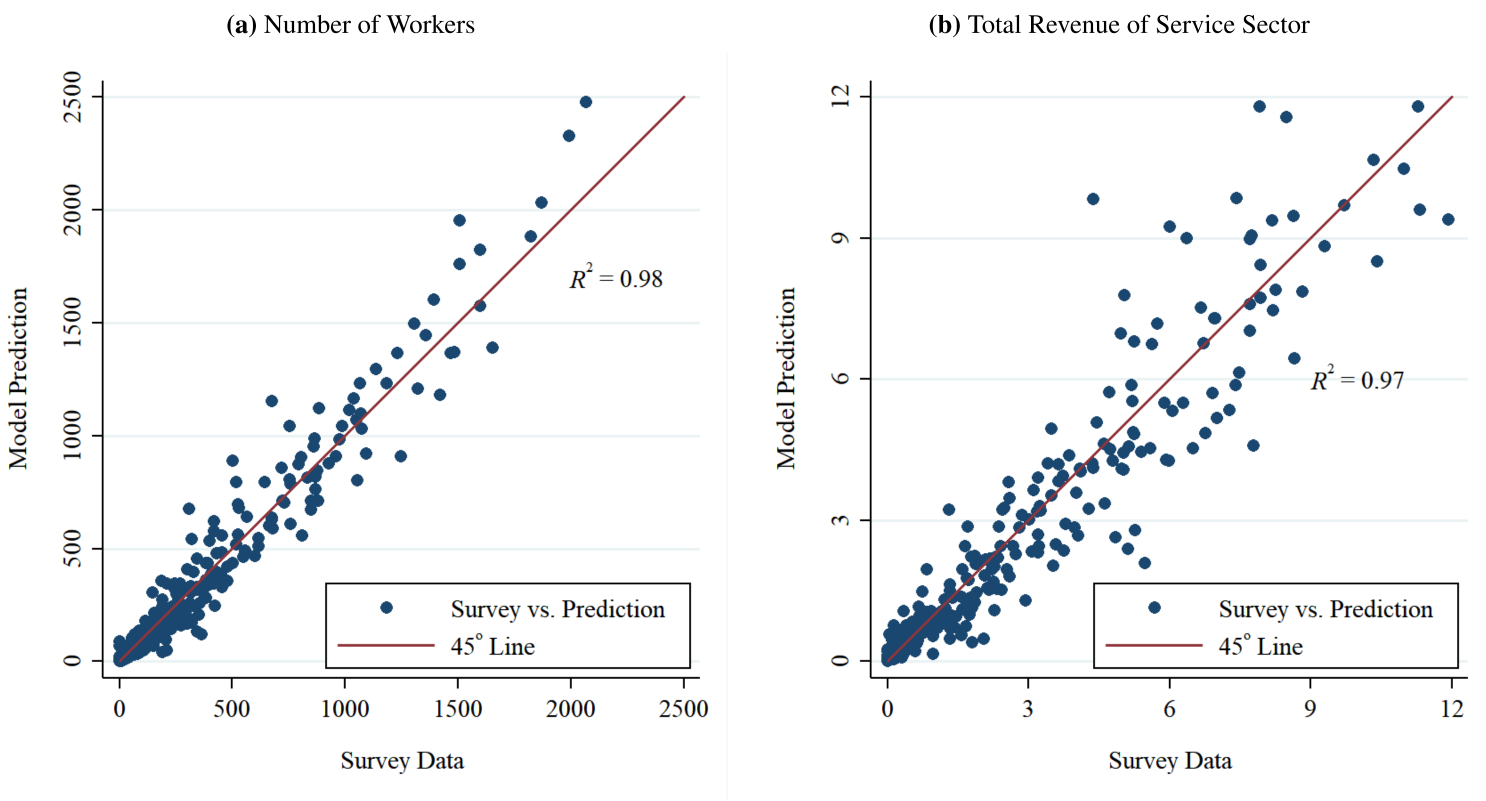
Notes: The figure plots the $PM_{2.5}$ concentration for each cell in Beijing in 2009 calculated from Hammer et al. (2020) and Van Donkelaar et al. (2019). Cells with deeper color denotes more polluted locations.

Figure A9: Schools and Parks



Notes: The figure plots locations of schools (red dots) and parks (green areas) in Beijing.

Figure A10: Survey Data vs. Predictions of Gravity Equations

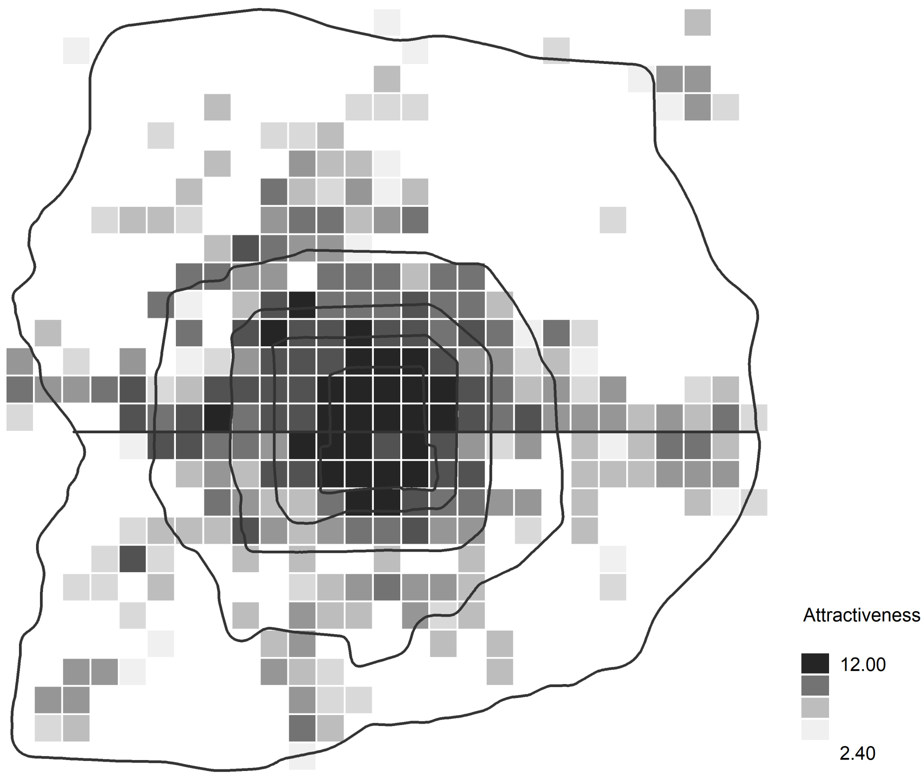


Notes: The figures show the relationship between model prediction (y-axis) and survey data (x-axis) for each location's (a) total number of workers and (b) total revenue of service sector. The unit for service revenue is million *yuan*.

The number of workers (L_m) is calculated from commuting probabilites ($\lambda^W_{mn|n}$) through Equation 15, and service revenue (E_m) from consumption probabilities ($\lambda^W_{jn|n}$) through Equation 14. For model predictions, observed commuting probabilities ($\lambda^W_{mn|n}$) and consumption probabilities ($\lambda^W_{jn|n}$) are replaced with their predictions from the gravity equations specified as Equation 17, without the error term.

Prediction errors in number of workers (L_m) and service revenue (E_m) are completely driven by prediction errors in commuting probabilities ($\lambda^W_{mn|n}$) and consumption probabilities ($\lambda^W_{jn|n}$), respectively.

Figure A11: Locations' Overall Attractiveness



Notes: The figure plots locations' overall attractiveness as residence, measured by its residential density and housing price,

$$Attractiveness_n = (\lambda_n^B)^{\frac{1}{\theta_B}} P_{nH}^{\alpha_H}.$$

Figure A12: Average Welfare Impacts by Age Groups

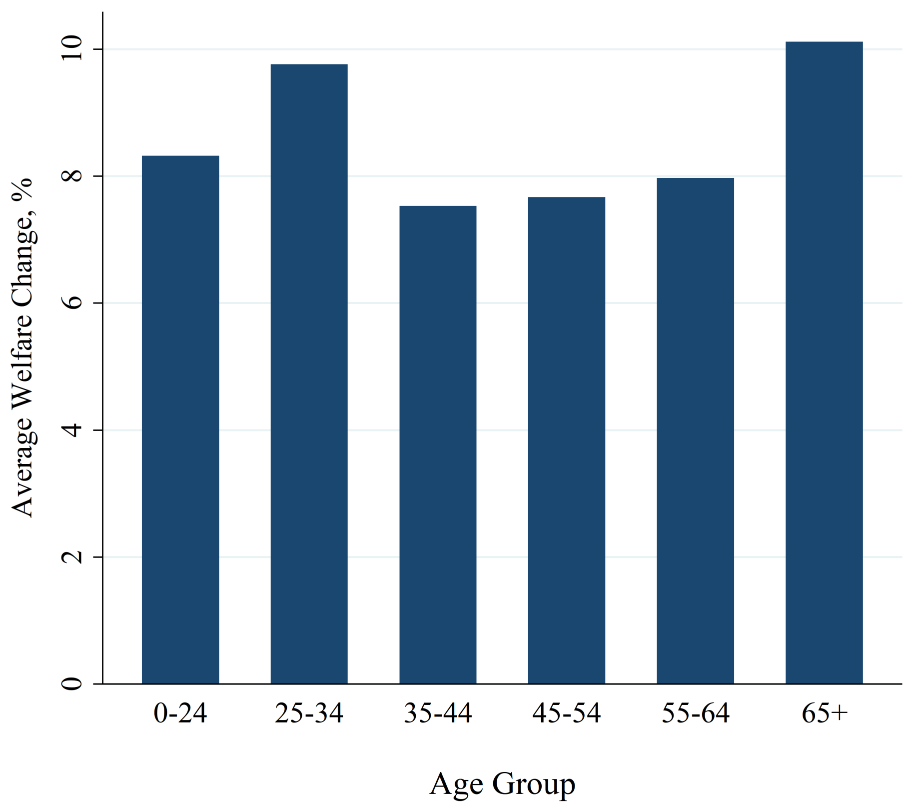


Figure A13: Average Welfare Impacts by Income Groups

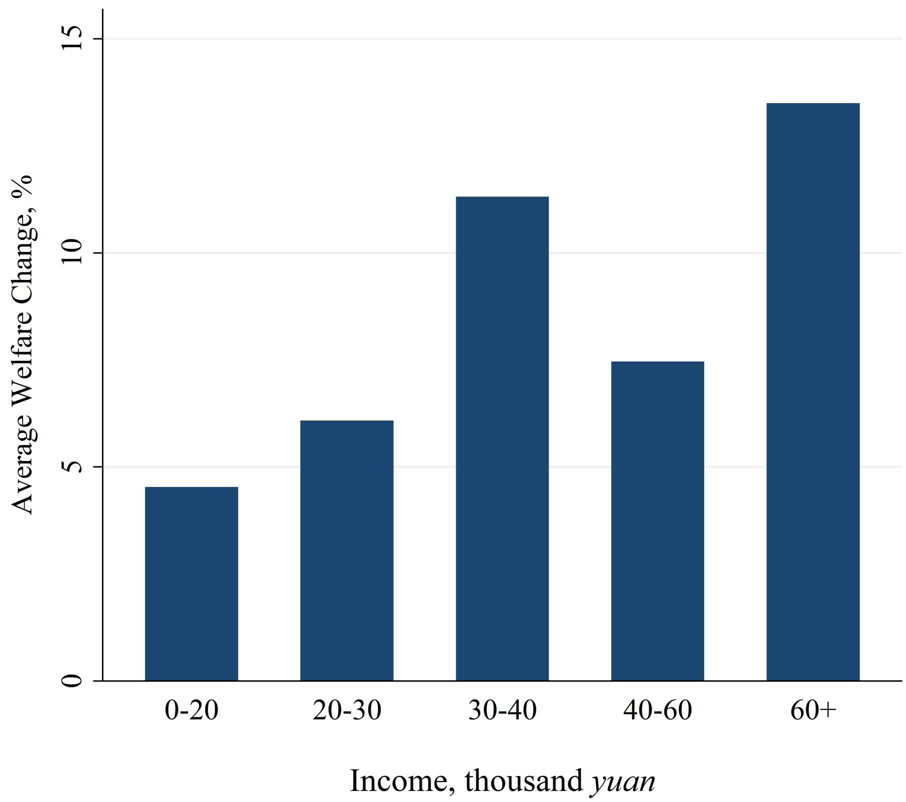
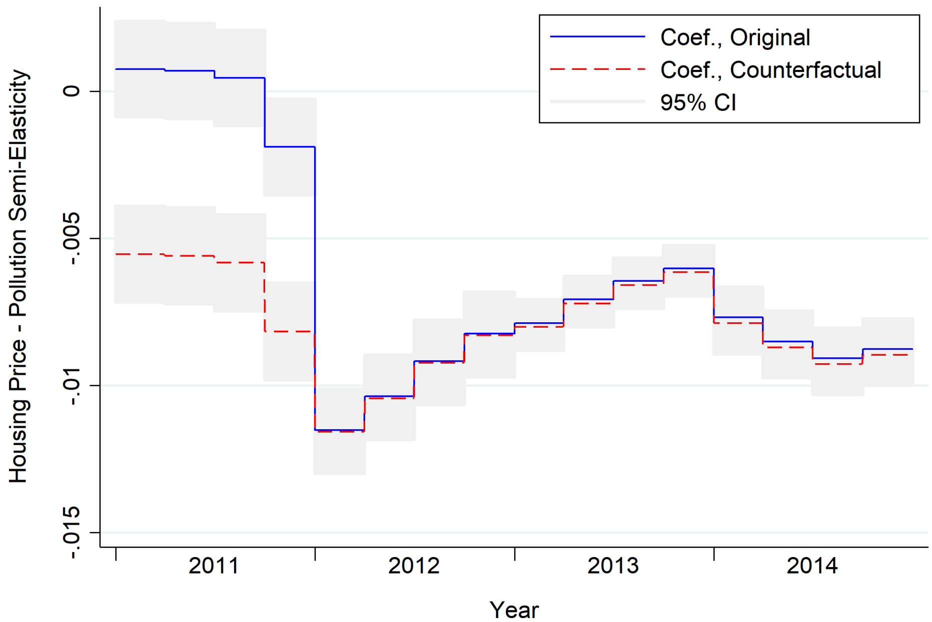


Figure A14: Counterfactual Event Study: Semi-Elasticity of Housing Price w.r.t Air Pollution



Notes: The figure plots quarterly semi-elasticity of housing price with respect to air pollution for Beijing's housing transactions between 2011 and 2014. Blue line plots the coefficient estimates using observed housing price in the sample. Red dash line plots the coefficient estimates with counterfactual housing prices, where unit housing price before Jan. 2012 is adjusted with the counterfactual changes as plotted in Figure 5g. Average of coefficients from the original event study prior to 2012 is normalized to zero. Controls include cell FEs, transaction year-month FEs, quadratic functions of unit and complex size, as well as other unit and complex characteristics (number of rooms, distance to nearest subway station at transaction date, school district, complex size and number of buildings).

Table A1: Robustness Checks for Decomposition of Residential Amenity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	2010	2014	2010	2014	2010	2014	2010 & 2014		
Proximity index for									
Schools			0.11*	0.14**	0.07	0.09			
			(0.07)	(0.06)	(0.07)	(0.06)			
Hospitals			0.16**	0.16***	0.07	0.08			
			(0.07)	(0.06)	(0.07)	(0.06)			
Parks			-0.08	0.18***	-0.05	0.05			
			(0.07)	(0.06)	(0.07)	(0.06)			
Air pollution $_{year-1}$	-0.02	-0.20***	-0.04	-0.24***	0.04	-0.25***	0.001	0.02	-0.26
	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.18)
Air pollution $_{year-1}$ $\times$ $\mathbb{1}\{2014\}$							-0.13*	-0.13*	-0.10
							(0.07)	(0.07)	(0.18)
District FEs					Yes	Yes		Yes	
Cell FEs									Yes
Year FEs							Yes	Yes	Yes
N	238	237	238	237	238	237	370	370	370
R^2	0.04	0.08	0.05	0.13	0.26	0.34	0.02	0.29	0.72

Notes:

The dependent variable measures residential amenities $\mathbb{B}$. Coefficients are standardized beta coefficients. Residential amenity is calculated as a location's attractiveness net of its commuting and consumption accessibility.

Proximity indices of amenity J for cell n are constructed as

$$index_n^J = \sum_{j \in J} \frac{1}{d_{nj}} x_j,$$

where J denotes the set of a given amenity (e.g. schools, hospitals, or parks); d_{nj} denotes the distance between cell n and amenity j; x_j denotes the quality of the amenity (fixed at 1 for schools and hospitals). For parks, I treat each cell as a potential amenity provider and use the area of green space in each cell as the quality measure x_j. Distances and areas are measured in km and km^2, respectively. Proximity indices are scaled up by 100 in regressions. Proximity indices are time-invariant.

Air pollution $_{year-1}$ denotes the average level of $PM_{2.5}$ concentration for the cell in the previous year. $\mathbb{1}\{2014\}$ is the indicator variable for year 2014.

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A2: General Equilibrium Elasticities

	% Change in							
	Number of Residents	Number of Workers	Area of Floor Space for Residential Use	Area of Floor Space for Production Use	Price of Floor Space	Average Wage of Employed Workers	Expected Income of Residents	Real Income of Residents
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Air Pollution, 2009	-.027***	-.0095***	-.013***	-.013***	-.003***	.00039	.0016***	.0033***
	(.0032)	(.0017)	(.0029)	(.0029)	(.00063)	(.0014)	(.00035)	(.00071)
N	346	626	260	296	356	616	316	260
R^2	.17	.05	.072	.069	.059	.00012	.059	.078

Notes: Each observation is a location cell. The dependent variables are changes in endogenous variables between the counterfactual equilibrium and the original. The independent variable is $PM_{2.5}$ concentration level at each location in 2009. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B Regression-Based Variance Decomposition

Assume the following data generating process,

$$y = x_1 + x_2 + x_3,$$

where outcome y is determined by three factors x_1, x_2, and x_3.

I can decompose the variance in y as

$$\begin{aligned}\text{var}(y) &= \text{cov}(y,y) \\ &= \text{cov}(x_1 + x_2 + x_3, y) \\ &= \text{cov}(x_1,y) + \text{cov}(x_2,y) + \text{cov}(x_3,y),\end{aligned}$$

or equivalently,

$$1 = \frac{\text{cov}(x_1,y)}{\text{var}(y)} + \frac{\text{cov}(x_2,y)}{\text{var}(y)} + \frac{\text{cov}(x_3,y)}{\text{var}(y)},$$

where $\frac{\text{cov}(x_k,y)}{\text{var}(y)}$ denotes the part of variation in y that can be explained by the comovement between outcome y and the k-th component (x_k).

I can estimate $\frac{\text{cov}(x_k,y)}{\text{var}(y)}$ from OLS regression with the following specification where x_k is the dependent variable and y is the independent variable,

$$x_k = \beta_0 + \beta_k y + \varepsilon,$$

and

$$\widehat{\beta}_k \xrightarrow{p} \beta_k = \frac{\text{cov}(x_k,y)}{\text{var}(y)}.$$

C Exact-hat Algebra

In the notation below, the changes between a variable in the original equilibrium (z) and its counterpart in the counterfactual equilibrium (z') are defined as $\widehat{z} = \frac{z'}{z}$ and $\Delta z = z' - z$. And the goal is to derive z' as functions of z and $\{\widehat{z}, \Delta z\}$.

To start with, I rewrite Equations 3, 5, and 7 and express changes in choice probabilities using changes in wages, price levels, travel costs, access measures, and residential amenities.

$$\widehat{\lambda}^W_{nm|n} = \frac{\left(\widehat{w}_m / \widehat{\kappa}^W_{nm}\right)^{\theta_W}}{\sum_{l \in N} \left(\widehat{w}_l / \widehat{\kappa}^W_{nl}\right)^{\theta_W} \lambda^W_{nl|n}},$$

$$\widehat{\lambda}^S_{nj|n} = \frac{\left(\widehat{P}_{jS} \widehat{\kappa}^S_{nj}\right)^{-\theta_S}}{\sum_{l \in N} \left(\widehat{P}_{lS} \widehat{\kappa}^S_{nl}\right)^{-\theta_S} \lambda^S_{nl|n}},$$

$$\widehat{\lambda}^B_n = \frac{\left(\widehat{B}_n \widehat{\mathbb{W}}_n \widehat{\mathbb{S}}_n / \widehat{P}^{\alpha_H}_{nH}\right)^{\theta_B}}{\sum_{l \in N} \left(\widehat{B}_l \widehat{\mathbb{W}}_l \widehat{\mathbb{S}}_l / \widehat{P}^{\alpha_H}_{lH}\right)^{\theta_B} \lambda^B_l},$$

where changes in commuting access and consumption access are derived from Equations 4 and 6 as

$$\widehat{\mathbb{W}}_n = \left[\left(\widehat{w}_n / \widehat{\kappa}^W_{nn}\right)^{\theta_W} / \widehat{\lambda}^W_{nn|n}\right]^{\frac{1}{\theta_W}},$$

$$\widehat{\mathbb{S}}_n = \left[\left(\widehat{P}_{nS} \widehat{\kappa}^S_{nn}\right)^{-\theta_S} / \widehat{\lambda}^S_{nn|n}\right]^{\frac{\alpha_S}{\theta_W}}.$$

The overall utility difference combines changes in amenities, commuting access, consumption access, and housing prices, weighted by the residential share,

$$\widehat{\bar{U}} = \left[\sum_{l \in N} \left(\widehat{\mathbb{B}}_l \widehat{\mathbb{W}}_l \widehat{\mathbb{S}}_l / \widehat{P}^{\alpha_H}_{lH}\right)^{\theta_B} \lambda^B_l\right]^{\frac{1}{\theta_B}}. \tag{1}$$

Rewriting results from producers' profit maximization in Equation 9, I can derive changes in prices and wages $\{\widehat{P}_{mH}, \widehat{P}_{mS}, \widehat{w}_m\}$, which should satisfy

$$\widehat{P}_{mS} = \frac{1}{\widehat{A}_m} \widehat{w}^{\beta}_m \widehat{P}^{1-\beta}_{mH},$$

or equivalently,

$$\widehat{w}_m = \left(\frac{\widehat{P}_{mS}\widehat{A}_m}{\widehat{P}_{mH}^{1-\beta}} \right)^{\frac{1}{\beta}}.$$

From the market clearing conditions, I can derive the price change in non-tradable goods as

$$\widehat{P}_{mS} = \frac{\widehat{E}_m}{\widehat{A}_m \widehat{\tilde{L}}_m^{\beta} \widehat{H}_{mS}^{1-\beta}},$$

where $\widehat{E}_m$ denotes the change in firms' total revenue and

$$\widehat{E}_m = \frac{\sum_n \lambda'^{W}_{nm|n} \mathbb{W}'_n R'_n}{\sum_n \lambda^{W}_{nm|n} \mathbb{W}_n R_n}.$$

In the labor and housing market, changes in demands can be derived as

$$\widehat{\tilde{L}_m} = \frac{\widehat{E}_m}{\widehat{w}_m},$$
$$\widehat{H_{mS}} = \frac{\widehat{E}_m}{\widehat{P}_{mH}},$$
$$\widehat{H_{nB}} = \frac{\widehat{\mathbb{W}_n} \widehat{R}_n}{\widehat{P}_{nH}}.$$

and changes in aggregated demand for floor space is

$$\widehat{H}_m = \frac{\widehat{H}_{mS} H_{mS} + \widehat{H}_{mB} H_{mB}}{H_{mS} + H_{mB}}.$$

From profit maximization conditions of the building sector, changes in housing price and floor space supply is governed by a constant supply elasticity, and

$$\widehat{P}_{mH} = \widehat{H}_m^{\frac{1-\mu}{\mu}}.$$

From residential probabilities and workplace choices, changes in labor supply can be derived as

$$\widehat{L}_m = \frac{\sum_n \lambda'^{W}_{nm|n} R'_n}{\sum_n \lambda^{W}_{nm|n} R_n}.$$

From Equations 11 and 12, externalities regarding productivity and common amenities should follow

$$\widehat{A}_m = \widehat{L}_m^{\eta_W},$$

$$\widehat{B}_n = \widehat{R}_n^{\eta_B}.$$

Finally, under the assumption of the closed-city model, the city's total population is a constant, and the number of residents at each location is proportional to its residential probability.

$$\widehat{Pop} = 0,$$

$$\text{and } \widehat{R}_n = \widehat{\lambda}_n^B.$$