

Efficiency and Equity Impacts of Urban Transportation Policies with Equilibrium Sorting

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Outline

Introduction

Data Description

Empirical Equilibrium Sorting Model

Estimation Results

Counterfactual Analysis

Conclusion

Motivation

- The crucial role of transportation in shaping the urban spatial structure and the organization of economic activity.
- Traffic congestion with severe economic consequences.
- Local governments have implemented a variety of policies to address urban traffic congestion.
 - Broader impacts on the urban spatial structure through household relocation in the medium to long run.

This paper: to understand the efficiency and equity impacts of urban transportation policies while accounting for sorting responses and endogenous congestion.

Context: Beijing, which has a population of 21.5 million and has routinely ranked as one of the most congested and polluted cities in the world.

Policies to address growing urban traffic congestion in Beijing:

- Driving restrictions [command and control demand side policy]
- Congestion price [market-based demand side policy]
- Investment in subway and rail transportation infrastructure [supply side policy]

Key Findings

1. While all three policies are designed to reduce congestion, they exhibit different and sometimes opposite impacts on the spatial patterns of residential locations and equilibrium housing prices.
2. Residential sorting can either strengthen or undermine the congestion-reduction potential of transportation policies.
3. Transportation policies generate different welfare implications in the aggregate and across income groups.

- The first study in the empirical sorting literature to jointly model residential locations and travel mode choices and evaluate how these choices simultaneously determine both congestion and distance to work in equilibrium.
- Relates to the recent advances using quantitative spatial equilibrium (QSE) models to explore the role of transportation in urban systems.
- Provides a micro-foundation that bridges the short-run and long-run policy impacts in transportation studies.

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Data Description

- Commuter-level Data

- Household-level Data

- Commuting Route, Speed, and Congestion

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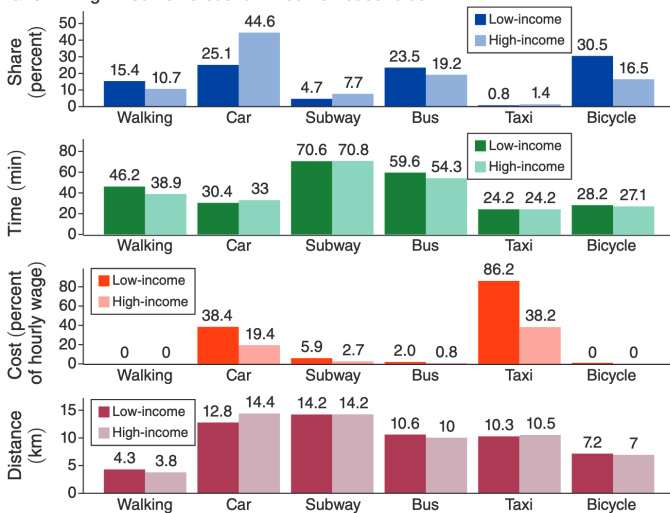
Conclusion

The Beijing Household Travel Surveys (BHTS), 2010 and 2014.

- Data on **individual and household demographics** and a travel diary on all trips taken during the preceding 24 hours.
- Detailed information for each trip by each commuting member of a household, including the origin and destination, departure and arrival time, trip purpose, and travel mode used.
- Processing
 - Six travel modes: walk, bike, bus, subway, car, and taxi
 - Attributes including the travel time, travel distance, and monetary cost for all travel modes in commuters' choice set.

Travel Patterns for Commuting Trips by Income Group

Panel B. High-income versus low-income households

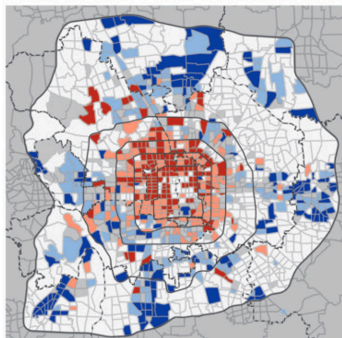


Housing mortgage data from 2006-2014:

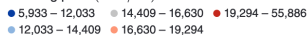
- Detailed information on **housing attributes** such as the property size, age, street address, transaction price, and date when the mortgage was signed.
 - Construct measures of proximate amenities (e.g., schools and parks)
- **Household demographics** including income, age, gender, marital status, residency status (hukou), and work addresses of primary borrower and co-borrower if one is present.
- Selection issues from subsample of mortgage dataset → use weighted sample

Spatial Pattern of Housing and Household Attributes

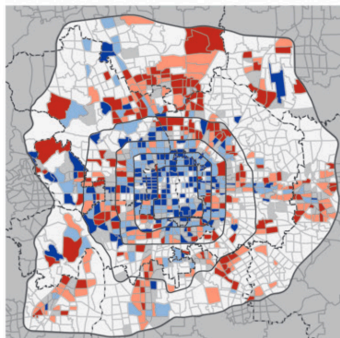
Panel A. Housing price ($\text{¥}/\text{m}^2$)



Housing price (rmb/m^2)



Panel B. Housing size (m^2)



Housing size (m^2)



► Distance to work, monthly household income

Household's Choice Set

- As home buyers: the unrealistic choice set is **all properties** listed on the market
- Adjustment: to include the purchased home and a 1 percent sample of houses randomly chosen from those sold during a two-month window around the purchase date → over 13 million route-mode combinations

Commuting Route, Speed, and Congestion

- Commuting routes: assume households follow the routes recommended by the Baidu (2019) and Gaode (2019) APIs.
- Driving speed: constructed using Baidu APIs vary by commuting routes.
- Congestion: measured by traffic density, constructed as the mileage-weighted number of vehicles on the road.
- The effect of congestion on speed: governed by the speed-density elasticity \rightarrow limited heterogeneity in speed-density elasticity across regions during rush hour.

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- Housing Demand

- Choice of Travel Mode

- Market-Clearing Conditions and the Sorting Equilibrium

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Empirical Equilibrium Sorting Model

How household members choose commuting modes and residential locations.

- Residential locations determine households' commute distances, which affect driving demand and contribute to traffic congestion.
- Traffic congestion impacts the desirability of different residential locations and directly influences housing demand.

Assumption: work locations are fixed ex ante and do not change.

Housing Demand

A characteristic-based housing demand model.

Utility function for **household** i choosing housing unit j , conditioning on work locations:

$$\max_{\{j \in \mathcal{J}_i\}} U_{ij} = \alpha_i p_j + \mathbf{x}_j' \beta_i + \sum_k \phi_{ik} EV_{ijk}(v_{ijk}) + \xi_j + \varepsilon_i \quad (1)$$

- \mathcal{J}_i : the choice set of housing units available to household i
- p_j : price of housing unit j
- \mathbf{x}_j : vector of **observed** housing attributes
- Commuting members within household, $k \in \{\text{male borrower, female borrower}\}$
- $EV_{ijk}(v_{ijk})$: the expected commuting utility, depends on the driving speed v_{ijk}
- ξ_j : unobserved housing attributes
- ε_i : i.i.d. error term with a type I extreme value distribution

Housing Demand: Random Coefficients

- α_i : the household-specific price coefficient

$$\alpha_i = \alpha_1 + \alpha_2 \times \ln(y_i)$$

- β_i : household preferences over housing attributes

$$\beta_{il} = \bar{\beta}_l + \mathbf{z}_i' \beta_l$$

- \mathbf{z}_i : vector of household demographics
- ϕ_{ik} : the ease-of-commute preference

$$\phi_{ik} = \bar{\phi}_k + \phi_k \zeta_{ik}$$

- ζ_{ik} : i.i.d. normal

The probability that household i chooses home j :

$$P_{ij}(\mathbf{p}, \mathbf{v}) = h(\mathbf{EV}(\mathbf{v}), \mathbf{p}, \mathbf{x}, \xi, \mathbf{z}_i) \quad (2)$$

Choice of Travel Mode

Utility-maximizing individuals in a household choose from six commuting modes (walk, bike, bus, subway, car, and taxi) based on the trip time and financial costs.

Individual i 's utility of commuting from home j to work using mode choice m :

$$\max_{m \in \mathcal{M}_{ij}} u_{ijm} = \theta_{im} + \gamma_1 \cdot \text{time}_{ijm}(v_{ij}) + \gamma_2 \cdot \text{cost}_{ijm}/y_i + \mathbf{w}'_{ijm}\eta + \varepsilon_{ijm} \quad (3)$$

- \mathcal{M}_{ij} : the choice set of transportation modes available to individual i 's work commute
- θ_{im} : the mode-specific random coefficients, have a normal distribution with mean μ_m and variance σ_m^2 , captures unobserved preferences
- \mathbf{w}_{ijm} : a rich set of interactions between mode dummies and year-fixed effects, trip attributes, and commuter demographics
- ε_i : i.i.d. error term with a type I extreme value distribution

Choice of Travel Mode

- γ_{1i} : time preference, follows a chi-squared distribution with mean μ_γ
- γ_2/y_i : individual's sensitivity to the monetary costs of commuting
- VOT: the value of time, $\frac{\gamma_{1i}}{\gamma_2} \cdot y_i$

The probability that individual i chooses mode m for the commute to work, conditional on home location j :

$$R_{ijm}(v_{ijm}) = r(\mathbf{time}(\mathbf{v}), \mathbf{cost}/y_i, \mathbf{w}_{ijm}) \quad (4)$$

The **ex ante** expected commuting utility:

$$\begin{aligned} EV_{ijk}(v_{ijk}) &= \mathbb{E}_{\varepsilon_{ijm}} \left[\max_{m \in \mathcal{M}_{ij}} u_{ijm}(v_{ij}) \right] \\ &= \log \left(\sum_{m \in \mathcal{M}_{ij}} \exp \theta_{im} + \gamma_{1i} \cdot time_{ijm}(v_{ij}) + \gamma_2 \cdot cost_{ijm}/y_i + \mathbf{w}'_{ijm} \eta \right) \end{aligned} \quad (5)$$

Market-Clearing Conditions and the Sorting Equilibrium

Interactions between housing market and transportation sector:

- The **spatial locations of households** affect the distance of work commutes and the choice of travel mode and hence congestion and driving speeds in the **transportation sector**.
- The level of **traffic congestion** that is determined in the transportation sector affects the attractiveness of residential locations through the commuting utility as discussed above, which, in turn, determines **households' sorting decisions** and shapes their spatial distribution.

Aggregate housing demand:

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

Housing supply (two scenarios):

1. The housing supply is fixed: $S_j(p) = 1$
2. Housing supply has a constant elasticity and adjusts at the neighborhood level in response to the average price within the neighborhood

Transportation Sector

Traffic density (congestion): the aggregation over all households' driving demand:

$$D_{T,r}(\mathbf{p}, \mathbf{v}) \equiv \sum_i \sum_j \mathbf{I} \{ \{i \rightarrow j\} \cap r \} \cdot P_{ij}(\mathbf{p}, \mathbf{v}) \cdot ([R_{ij,car}(\mathbf{v}) \cdot \text{dist}_{ijr,car}] + [R_{ij,taxi}(\mathbf{v}) \cdot \text{dist}_{ijr,taxi}]) \quad (6)$$

- r : spatial granularity of the traffic density measure
 1. Citywide congestion
 2. Congestion at the ring-road-band level
 3. Congestion at the ring-road-quadrant level

The supply side: $S_{T,r}$ is the number of vehicles on the road in region r

- The travel speed \mathbf{v} can be sustained given Beijing's transportation technology and road capacity

Sorting Equilibrium

A vector of housing prices, \mathbf{p}^* , and a vector of driving speeds, \mathbf{v}^* , such that:

1. The housing market clears for all properties:

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

When housing supply adjusts at the neighborhood level:

$$D_n = \sum_{j \in n} P_j(\mathbf{p}^*, \mathbf{v}^*) = S_n(\mathbf{p}^*), \forall n$$

2. The transportation sector clears for every region r :

$$D_{T,r}(\mathbf{p}^*, \mathbf{v}^*) = S_{T,r}(\mathbf{v}^*), \forall r \quad (8)$$

The existence of a sorting equilibrium follows Brouwer's fixed point theorem.

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- Housing Location Choice

- Speed-Density Elasticity

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Commuting Mode Choice

- Key parameters of interest: time and monetary cost preferences
- Method: Simulated maximum likelihood estimation
- **Assume:** the error term ε_{ijm} in equation (3) is uncorrelated with commuting trips' monetary costs and travel time

Estimation Results for Travel Mode Choices

	logit			Random coefficient		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Travel time</i> (γ_1)	-1.194 (0.082)	-0.270 (0.006)	-0.191 (0.006)			
<i>Travel cost/hourly wage</i> (γ_2)	-1.578 (0.324)	-0.788 (0.028)	-0.565 (0.034)	-1.411 (0.041)	-1.424 (0.052)	-2.531 (0.065)
Random coefficients on travel time (μ_γ)						
<i>Travel Time</i>				-0.955 (0.008)	-0.885 (0.008)	-0.931 (0.012)
Random coefficients on mode dummies (σ_m)						
<i>Driving</i>					3.394 (0.049)	3.391 (0.054)
<i>Subway</i>						4.470 (0.142)
<i>Bus</i>						3.851 (0.056)
<i>Bike</i>						3.887 (0.054)
<i>Taxi</i>						4.203 (0.353)
Mode \times year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mode \times trip related FE		Yes	Yes	Yes	Yes	Yes
Mode \times demographic FE			Yes	Yes	Yes	Yes
log-likelihood	-116,287	-109,929	-91,119	-87,353	-85,099	-77,706
Implied mean VOT	0.757	0.342	0.339	1.760	1.615	0.956
Implied median VOT	0.757	0.342	0.339	1.557	1.429	0.846

Housing Location Choice

Estimate housing demand use mortgage data

$$U_{ij} = \mu_{ij} + \delta_j + \varepsilon_{ij} \quad (9)$$

$$\mu_{ij} = \alpha_2 \ln(y_i) p_j + \sum_l x_{jl} \cdot \mathbf{z}_i' \beta_l + \sum_k \phi_{ik} EV_{ijk}(v_{ijk}) \quad (10)$$

$$\delta_j = \alpha_1 p_j + \mathbf{x}_j' \beta_1 + \xi_j \quad (11)$$

- μ_{ij} : household-specific utility
 - δ_j : the population-average utility
1. Uses simulated MLE with a nested contraction mapping to estimate the household-specific parameters.
 2. Uses linear IV for coefficients in the mean utility (linear parameters).

Housing Demand-Nonlinear Parameters

TABLE 4—HOUSING DEMAND-NONLINEAR PARAMETERS FROM SIMULATED MLE

	No <i>EV</i> (1)		With <i>EV</i> (2)		<i>EV</i> and random coef. (3)	
	Para	SE	Para	SE	Para	SE
Demographic interactions						
<i>Price</i> (¥mill.) $\times \ln(\text{income})$	0.965	0.007	1.005	0.014	1.030	0.016
<i>Age</i> in 30–45 $\times \ln(\text{distance to key school})$	−0.329	0.004	−0.391	0.011	−0.420	0.013
<i>Age</i> > 45 $\times \ln(\text{distance to key school})$	−0.074	0.009	−0.111	0.025	−0.123	0.026
<i>Age</i> in 30–45 $\times \ln(\text{home size})$	1.343	0.014	1.443	0.026	1.486	0.030
<i>Age</i> > 45 $\times \ln(\text{home size})$	2.394	0.028	2.665	0.070	2.746	0.060
<i>EV</i> _{Male}			0.708	0.015	0.755	0.016
<i>EV</i> _{Female}			0.833	0.017	0.893	0.019
Random coefficients						
$\sigma(EV_{Male})$					0.379	0.019
$\sigma(EV_{Female})$					0.482	0.018
log-likelihood	−206,829		−170,057		−168,808	

IVs for housing prices:

1. The number of properties that are located in a different complex and within 3 km of unit j and sold within a two-month window around property j 's sale; [donut instruments]
2. The average attributes of these properties; [donut instruments; BLP instrument]
3. The interaction between the average attributes and the odds of winning the license plate lottery.

Housing Demand-Linear Parameters

TABLE 5—HOUSING DEMAND-LINEAR PARAMETERS

	OLS (1)	OLS (2)	IV1 (3)	IV2 (4)	IV2 + IV3 (5)	ALL (6)
<i>Price</i> (¥mill.)	−2.24 (0.186)	−2.191 (0.184)	−7.091 (1.640)	−6.283 (0.867)	−6.454 (0.583)	−6.596 (0.534)
<i>ln(home size)</i>	−3.648 (0.257)	−3.797 (0.261)	4.721 (2.927)	3.331 (1.505)	3.631 (1.022)	3.879 (0.969)
<i>Building age</i>	−0.043 (0.007)	−0.029 (0.006)	−0.144 (0.040)	−0.125 (0.020)	−0.129 (0.014)	−0.132 (0.013)
<i>Floor area ratio</i>	−0.006 (0.034)	−0.009 (0.025)	−0.019 (0.036)	−0.023 (0.032)	−0.023 (0.033)	−0.023 (0.034)
<i>ln(dist. to park)</i>	0.21 (0.069)	0.074 (0.057)	−0.475 (0.222)	−0.389 (0.117)	−0.408 (0.101)	−0.424 (0.103)
<i>ln(dist. to key school)</i>	0.95 (0.080)	0.782 (0.137)	0.210 (0.213)	0.323 (0.139)	0.304 (0.121)	0.288 (0.118)
<i>District-month-of-sample</i> FE	Y	Y	Y	Y	Y	Y
<i>Neighborhood</i> FE		Y	Y	Y	Y	Y
First-stage Kleinberg-Paap <i>F</i>			9.88	10.48	14.22	14.22
<i>p</i> -value: overidentification test				0.03	0.10	0.19
Avg. housing demand price elasticity			−2.42	−1.40	−1.61	−1.79

Assuming constant speed-density elasticity and estimate using hourly data from remote traffic microwave sensors.

$$\ln(v_{st}) = e_{T,r} \times \ln(\text{Traffic Density}_{st}) + \mathbf{x}'_{st}\beta_T + \varepsilon_{st} \quad (12)$$

- Notation:
 - v_{st} : road segment s 's speed in km/h by hour t
 - $\text{Traffic Density}_{st}$: the number of vehicles per lane-km
 - \mathbf{x}'_{st} : weather-related variables and time and spatial fixed effects
- IV: a dummy for days when vehicles with a license number ending in 4 or 9 are restricted from driving.
- Finding: heterogeneity in speed-density elasticity across regions is limited

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Welfare Decomposition

Households' ex ante welfare:

$$W_i = \mathbb{E}_{\epsilon_{ij}} \left[\max_{j \in \mathcal{J}_i} U_{ij}(\mathbf{p}, \mathbf{v}, \text{cost}_i) \right] \quad (13)$$

Transportation policies directly affect commuting costs. The total derivative of household welfare w.r.t. commuting costs:

$$\begin{aligned}
 (14) \quad \frac{dW}{dcost} &= \underbrace{\left. \frac{\partial W}{\partial cost} \right|_{\mathbf{p}=\mathbf{p}_0, \mathbf{v}=\mathbf{v}_0}}_{(1) \text{ direct policy effect}} \\
 &+ \underbrace{\left. \frac{\partial W}{\partial \mathbf{v}'} \frac{\partial \mathbf{v}}{\partial cost} \right|_{\tilde{\mathbf{v}}}}_{(2) \text{ partial speed effect}} + \underbrace{\left. \frac{\partial W}{\partial \mathbf{v}'} \frac{\partial \mathbf{v}}{\partial cost} \right|_{D_T(\mathbf{v}^*)=S_T(\mathbf{v}^*)} - \left. \frac{\partial W}{\partial \mathbf{v}'} \frac{\partial \mathbf{v}}{\partial cost} \right|_{\tilde{\mathbf{v}}}}_{(3) \text{ rebound effect}} \\
 &\quad \underbrace{\hspace{10em}}_{(2) + (3) \text{ equil. speed effect}} \\
 &+ \underbrace{\left. \frac{\partial W}{\partial \mathbf{p}'} \frac{\partial \mathbf{p}}{\partial cost} \right|_{D(\mathbf{p}^*, \mathbf{v}^*)=1}}_{(4) \text{ equil. sorting effect}} + \underbrace{\left. \frac{\partial W}{\partial \mathbf{p}'} \frac{\partial \mathbf{p}}{\partial cost} \right|_{D(\mathbf{p}^*, \mathbf{v}^*)=S} - \left. \frac{\partial W}{\partial \mathbf{p}'} \frac{\partial \mathbf{p}}{\partial cost} \right|_{D(\mathbf{p}^*, \mathbf{v}^*)=1}}_{(5) \text{ housing supply effect}}.
 \end{aligned}$$

Policy Scenarios

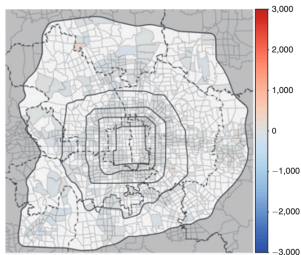
1. Driving restrictions: demand-side command-and-control policy
2. Congestion pricing: demand-side market-based policy
3. Subway expansion: supply-side policy
4. Subway expansion + driving restrictions: combined policy
5. Subway expansion + congestion pricing: combined policy

Simulation Results with Household Sorting

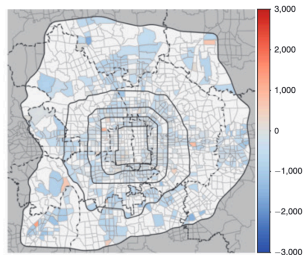
Income relative to the median	2008 Subway Network						2014 Subway Network					
	No Policy (1)		Driving restriction Δs from (1) (2)		Congestion pricing Δs from (1) (3)		Subway expansion Δs from (1) (4)		+Driving restriction Δs from (1) (5)		+Congestion pricing Δs from (1) (6)	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Panel A. Travel mode shares in percentage points and average speed												
Drive	41.65	21.44	−7.17	−3.4	−3.48	−5.39	−2.14	−1.66	−8.52	−4.62	−5.2	−6.4
Subway	9.02	10.77	1.29	0.7	0.84	0.96	4.62	6.06	5.79	6.44	5.24	6.83
Bus	22.44	30.47	1.78	0.6	0.57	1.24	−1.54	−2.53	0.31	−1.57	−0.76	−1.03
Bike	15.96	24.01	1.6	0.8	0.77	1.78	−0.8	−1.64	0.52	−0.94	−0.13	−0.13
Taxi	2.2	1.32	1.19	0.55	0.63	0.57	−0.16	−0.11	0.89	0.36	0.39	0.36
Walk	8.74	11.99	1.31	0.74	0.67	0.83	0.02	−0.13	1.01	0.32	0.46	0.37
Avg. Speed (km/h)	21.49		3.83		3.83		1.49		5.08		5.29	
Panel B. Sorting outcomes												
Distance to work (km)	18.56	15.66	0.01	0.01	−0.17	−0.06	0.36	0.18	0.41	0.17	0.15	0.12
Distance to subway (km)	5.33	4.3	−0.03	0.03	−0.03	0.03	−4.14	−3.44	−4.14	−3.44	−4.14	−3.44

Changes in Commuting Distance from Sorting

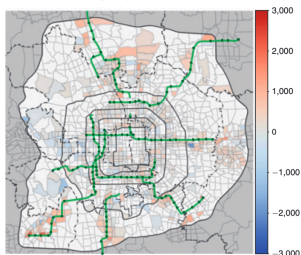
Panel A. Driving restriction



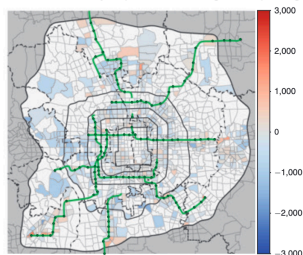
Panel B. Congestion pricing



Panel C. Subway expansion

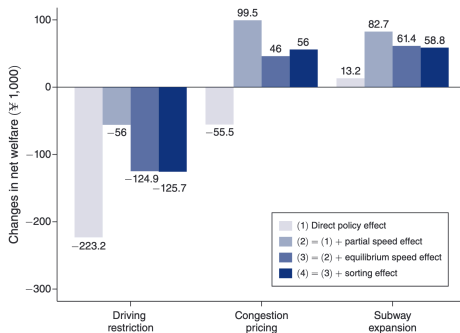


Panel D. Subway expansion + congestion pricing



Welfare Analysis

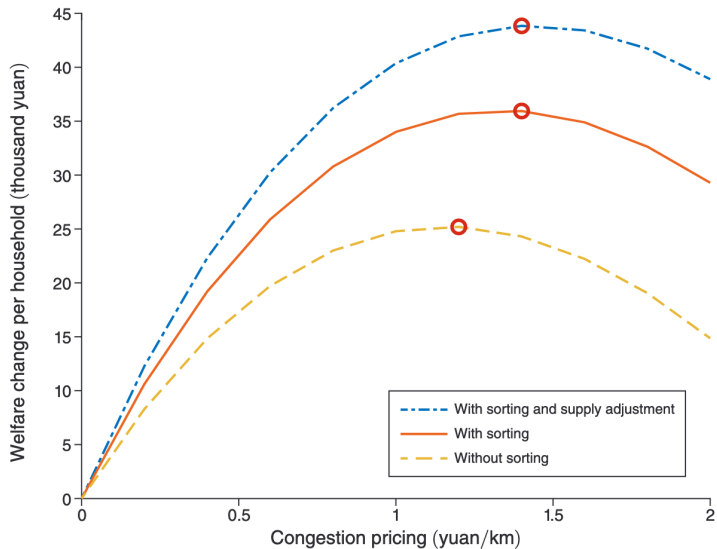
	2008 Subway Network						2014 Subway Network					
	No Policy (1)		Driving restriction Δ s from (1) (2)		Congestion pricing Δ s from (1) (3)		Subway expansion Δ s from (1) (4)		+Driving restriction Δ s from (1) (5)		+Congestion pricing Δ s from (1) (6)	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
<i>Panel C. Welfare changes per household (thousand ¥)</i>												
Consumer surplus (+)			-227.1	-32.7	-98.2	-73.1	220.3	100	-14	64	108.7	28.7
Toll revenue (+)					137.4	137.4					127.7	127.7
Subway costs (-)							103	103	103	103	103	103
Pollution reduction (+)			4.25	4.25	4.25	4.25	1.69	1.69	5.79	5.79	6.03	6.03
Net welfare			-222.8	-28.4	43.5	68.6	119.0	-1.3	-111.2	-33.2	139.4	59.4



Importance of Sorting, Endogenous Congestion, and Extensions

	Driving restriction			Congestion pricing			Subway expansion		
	Δ Speed	Δ Welfare (¥1000)		Δ Speed	Δ Welfare (¥1000)		Δ Speed	Δ Welfare (¥1000)	
Income relative to the median	(km/h)	High	Low	(km/h)	High	Low	(km/h)	High	Low
<i>Panel A. Sorting and endogenous congestion</i>									
With sorting (main results)	3.83	-222.8	-28.4	3.83	43.5	68.6	1.49	119.0	-1.3
Without sorting	3.82	-223.1	-26.8	3.61	32.1	59.6	1.76	106.7	16.0
With sorting but without endogenous congestion	5.47	-107.3	-4.4	5.15	118.1	81.0	2.36	158.8	6.4
<i>Panel B. Extensions and robustness checks</i>									
With sorting and housing supply response	3.85	-225.5	-27.9	4.02	56.3	72.8	0.95	64.0	-16.0
With ring-road-quadrant-level traffic density	3.46	-239.4	-31.8	3.38	24.7	67.5	1.25	104.9	-4.8
Without random coefficients	4.59	-1,447.6	-338.0	4.59	-406.9	-3.6	1.61	15.5	-42.5
With migration	4.65	-193.4	-22.6	4.63	77.1	75.7	0.73	82.0	-8.5
With consumption access	3.83	-297.8	-43.5	3.83	56.4	89.8	1.49	191.6	31.6

Optimal Congestion Pricing under the 2014 Subway Network



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Takeaways

1. Including the utility from the ease-of-commuting in housing demand dramatically improves the model fit.

Flexible preference heterogeneity, incorporating sorting responses, and modeling the joint equilibrium of the transportation sector and housing market.

2. Findings

- 2.1 Compared to driving restrictions, congestion pricing better incentivizes residents to live closer to their work locations.

- 2.2 Subway expansion does the opposite by increasing the separation between residences and workplaces.

3. Different policies generate drastically different efficiency and equity impacts. The combination of congestion pricing and subway expansion stands out as the best policy.

Limitations: potential implications for the labor market and firm locations.

Thanks!

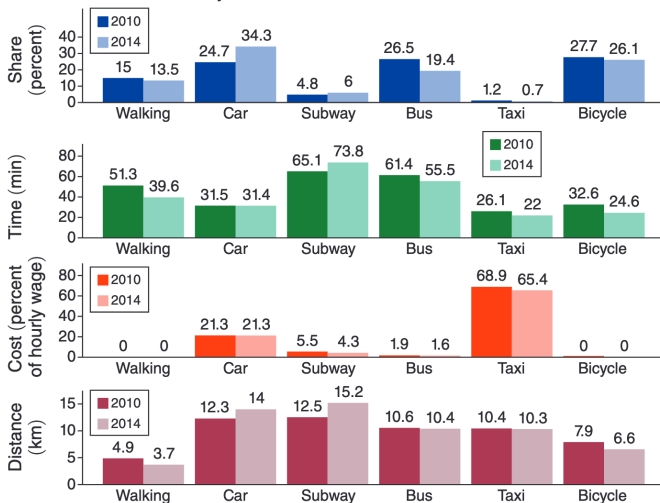
Commuter-level Data: Summary Statistics

TABLE 1—SUMMARY STATISTICS OF HOUSEHOLD TRAVEL SURVEY

	2010			2014		
	<i>N</i>	Mean	SD	<i>N</i>	Mean	SD
<i>Respondent characteristics</i>						
Income: < ¥ 50k	14,780	0.48	0.50	20,573	0.18	0.38
Income: [¥ 50k, ¥ 100k)	14,780	0.39	0.49	20,573	0.44	0.50
Income: > = ¥ 100k	14,780	0.13	0.34	20,573	0.38	0.49
Having a car (= 1)	14,780	0.44	0.50	20,573	0.62	0.49
Female (= 1)	14,780	0.44	0.50	20,573	0.43	0.50
Age (in years)	14,780	37.59	10.28	20,573	38.47	9.84
College or higher (= 1)	14,780	0.61	0.49	20,573	0.64	0.48
Home within fourth ring (= 1)	14,780	0.51	0.50	20,573	0.41	0.49
Workplace within fourth ring (= 1)	14,780	0.59	0.49	20,573	0.50	0.50
<i>Trip related variables</i>						
Travel time (hour)	30,334	0.87	1.06	42,820	0.74	0.98
Travel cost (¥)	30,334	2.47	5.55	42,820	3.83	6.96
Distance < 2 km	30,334	0.25	0.43	42,820	0.24	0.43
Distance in [2, 5 km)	30,334	0.27	0.45	42,820	0.26	0.44

Travel Patterns for Commuting Trips, Year 2010 versus Year 2014

Panel A. Year 2010 versus year 2014



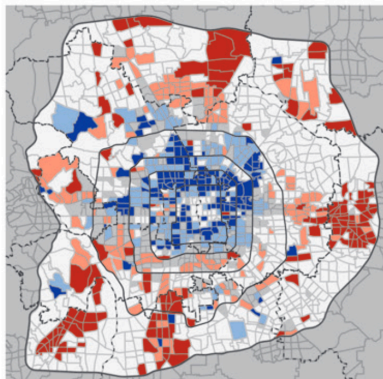
Household-level Data: Summary Statistics

TABLE 2—SUMMARY STATISTICS OF HOUSING DATA

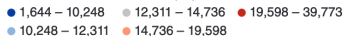
	Mean	SD	Min	Max
<i>Housing attributes</i>				
Transaction year	2011	1.89	2006	2014
Price (¥ 1,000/m ²)	19.83	9.56	5.00	68.18
Unit size (m ²)	92.68	40.13	16.71	400.04
Household annual income (¥1,000)	159.71	103.34	6.24	2,556.90
Primary borrower age	33.99	6.62	20.00	62.00
<i>Housing complex attributes</i>				
Distance to key school (km)	6.05	5.61	0.03	23.59
Complex vintage	2004	8	1952	2017
Green space ratio	0.32	0.06	0.03	0.85
Floor area ratio	2.56	1.12	0.14	16.00
Number of units	1,972	1,521	24	13,031
<i>Home-work travel variables</i>				
Walking distance (km)	14.10	9.51	0.00	62.92
Driving distance (km)	16.13	10.87	0.00	85.22
Home to subway distance (km)	2.13	2.31	0.04	28.37
Subway route distance (km)	15.17	10.70	0.00	68.40

Spatial Pattern of Housing and Household Attributes

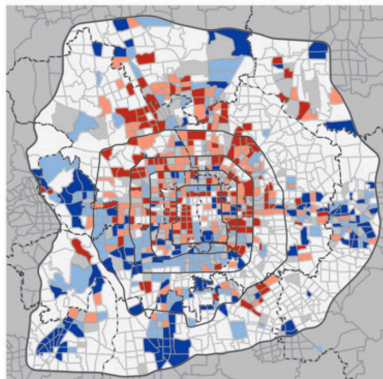
Panel C. Distance to work (m)



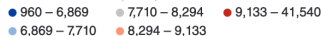
Driving distance to work (m)



Panel D. Monthly household income (¥)



Monthly income (rmb)



Environmental Considerations, Fisical Balance

- Environmental considerations

$$B_i = \sum_j \Pr(\text{Household } i \text{ buys property } j) \times B_{ij} \quad (14)$$

$$B_{ij} = \sum_{k=1}^K VKT_{ij} \times EF_{ijk} \times MD_k \quad (15)$$

- B_{ij} : pollution damage if household i resides in property j
- VKT_{ij} : commuting distance
- EF_{ijk} : emissions factor of pollutant k
- MD_k : marginal damage
- Fiscal balance: account for capital and operating costs for subway construction and congestion pricing

Changes in Housing Prices from Counterfactual Simulations

