Online Appendix for
Home Location Choices and the Gender Commute Gap
Not for Publication

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A Description of Supporting Data Sets

A.1 The 2015 Beijing Household Travel Survey

The Survey covers around 100,000 individuals from 40,000 households in Beijing. The Survey has information on individual and household demographic and economic characteristics, records where each respondent lives and works, and includes a travel diary that tracks each respondent's whereabouts on the day of survey. For each trip, the diary records the departure and arrival locations and times, and the modes of transportation used. From the travel diaries, we compile 62,697 commuting trips from 28,366 workers. The Survey also includes a roster and demographic characteristics of each household member, and household income, although it does not include individual income. The smallest identifiable geographic area in the Survey is the Transportation Analysis Zone (TAZ). Beijing, with an area of 6,490 square miles and a population of 21.5 million, is divided into approximately 2,000 TAZs. TAZs close to the city center are much smaller than those in the suburbs.

A "trip" is defined as the full length of a travel from the origin to the destination for a defined purpose. For example, a one-way commute is a trip. A trip can include multiple "legs," separated by stops. Travellers make stops during a trip to switch modes of transportation (such as interchange for a different bus route) or a quick stopover at some place (such as picking up breakfast at a nearby convenience store). The travel diary has detailed information on each leg of a trip, including departure time, arrival time, and the modes of transportation. We aggregate at the trip level, and define the mode of transportation for the whole trip using the leg that covers the longest distance. One-way commute time is calculated as the sum of travel time in each leg, including stoppage or wait time. Commute distance is the linear distance between the home TAZ and the work TAZ. If the person lives and works in the same TAZ, we impose a commute distance of 1 km.

A.2 Intra-decennial census of 2015

The 2015 "mini" census covers around 0.1% of the population. It is the first nationwide survey to include questions on commute. For those who are currently employed, it asks the usual commute time, mode of transportation, and the township of residence and workplace.[1] Commute distance is calculated as the linear distance between the centroids of home and work townships. For workers who live and work within the same township, we impose a commute distance of 1 km.

[1] China is divided into about 40,000 townships. Beijng is divided into 343 townships.

A.3 Comparisons across data sets

We compare the three data sets we have — the mortgage data, the Household Travel Survey, and the census — that speak to the gender commute gap. From all data sets, we include those who are between 25 and 59 years old and are currently working in non-agricultural industries. Table A.1 shows that compared with those represented in the Travel Survey and the census, individuals in the mortgage sample are younger, better educated, have a higher income, and commute longer distances. There are also some differences between the sample in the Travel Survey and that in the census, with respondents in the former older, having shorter commute distances, and more likely to drive to work. From the census, which covers the whole country, we see Beijing residents are much better educated than those in the rest of the country. Beijing residents commute almost twice as long, both by distance and by time, and they are more likely to use car or public transit for commute.

Measured either in time or distance, male workers consistently have longer commutes than female workers across all samples. Table A.2 shows that the gender commute gap in distance, after controlling for individual demographics, is between 12% and 27% across the samples, the gender gap in commute time is between 4% and 14%. Figure A.1 shows that the gender commute gap is prevalent across all provinces in China. Although data sets other than the mortgage sample do not speak to the cause of the gender commute gap, the comparison across those different data sets suggest that what we find in the paper is unlikely unique to the data we use.

A.4 Gender Commute Gap in Alternative Household Arrangements

The households in the main sample are those with both spouses working. The restriction to the sample is mandated by the research question: we need properly identified commutes from both spouses to define the gender gap. Nevertheless, this restriction also raises the concern of sample selection. Inspecting commute distances in other types of household arrangement helps present a more complete picture.

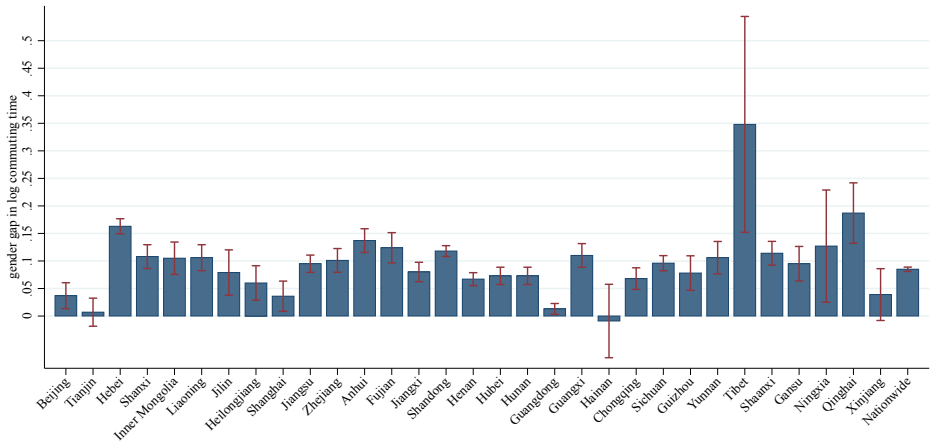
We first look at households in which either the husband or the wife does not work. For the non-working spouse, commute distance is not defined, so we cannot inspect the gender commute gap as we do in the rest of the paper. Instead, we compare husbands (wives) in households where the spouse does not work with those in dual-income households. There are many other differences between sole-earner households and dual-income households, so we control for detailed demographic characteristics to make them as comparable as possible. The first two columns of Table A.3 show that, compared with their counterparts in which the spouse is the sole earner, those in dual-income households have longer commutes. This is intuitive: With both spouses working, the household location choice reflects a balance between both spouses' commutes.

The mortgage data have few cases where there is only one borrower. Even in rare cases where there is only one borrower, we do not know whether the sole-borrower is unmarried or the he is married but the spouse is not listed as a co-borrower. To investigate the gender commute gap by marital status, we resort to the Household Travel Survey, in which about 8% of the respondents are not married. Columns 3 and 5 of Table A.3 show that gender gap in commute, either measured by time or distance, is about

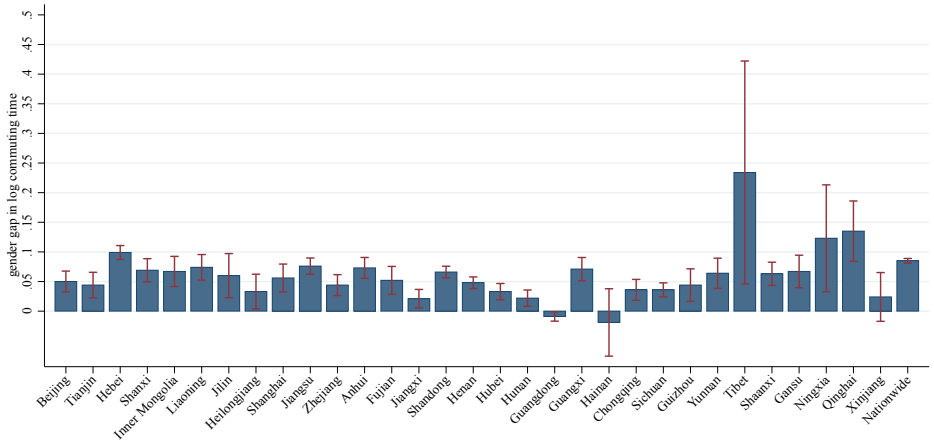
half among singles than among married people. Columns 4 and 6 further show that among those who are married, having children at home is associated with larger gender commute gaps. These results are consistent with the prediction that the gender commute gap is correlated with the division of labor in household production.

Figure A.1: Gender Gap in Commute Time by Province

Panel A



Panel B



Note: The data is from the 2015 intra-decennial census. The sample includes individuals between 25 and 59 years old who are currently employed in non-agricultural industries. Each bar presents the estimated coefficient associated with an indicator for men in each province. In Panel A, regressions include a set of age bin fixed effects and a set of education attainment fixed effect. In Panel B, regressions include an additional set of transportation mode fixed effects. Range bars indicate the 95% confidence intervals.

Table A.1: Summary Statistics from Various Data Sets

	mortgage		travel survey		Census, Beijing		Census, nationwide	
male ratio	.502		.560		.587		.601	
	male	female	male	female	male	female	male	female
age 25-34	.594	.674	.226	.276	.374	.453	.333	.381
	(.491)	(.469)	(.418)	(.447)	(.484)	(.498)	(.471)	(.486)
age 35-44	.292	.238	.272	.342	.298	.321	.310	.347
	(.455)	(.426)	(.445)	(.475)	(.457)	(.467)	(.463)	(.476)
age 45-59	.113	.088	.502	.381	.328	.226	.357	.272
	(.317)	(.283)	(.5)	(.486)	(.469)	(.418)	(.479)	(.445)
college degree	.525	.492	.332	.363	.297	.386	.096	.117
	(.499)	(.5)	(.471)	(.481)	(.457)	(.487)	(.294)	(.321)
married	1	1	.932	.930	.855	.842	.874	.880
	(0)	(0)	(.251)	(.254)	(.352)	(.365)	(.332)	(.325)
has kid[1]			.542	.557		.635		.714
			(.498)	(.497)		(.482)		(.452)
monthly income	6,744	5,314						
	(4,952)	(3,823)						
commute dist. (km)[2]	15.26	14.043	6.493	5.054	10.637	9.758	4.224	3.954
	(13.595)	(13.058)	(8.591)	(7.151)	(15.264)	(13.643)	(10.675)	(10.115)
commute time (min)			35.165	32.446	34.825	35.251	18.621	17.54
			(38.272)	(44.246)	(31.855)	(30.268)	(18.278)	(16.496)
mode of transportation								
car			.343	.194	.257	.157	.166	.097
			(.475)	(.396)	(.437)	(.364)	(.372)	(.296)
public transit			.207	.263	.301	.402	.106	.139
			(.405)	(.44)	(.459)	(.49)	(.307)	(.346)
bike/walk			.450	.543	.441	.441	.729	.764
			(.498)	(.498)	(.497)	(.496)	(.445)	(.424)
hhd. annual income (2015 yuan)								
$\leq$ 50k	.102		.252					
	(.303)		(.434)					
(50k, 100k]	.310		.449					
	(.462)		(.497)					
(100k, 150k]	.264		.187					
	(.441)		(.39)					
(150k, 200k]	.175		.066					
	(.38)		(.248)					
$\geq$ 200k	.151		.046					
	(.358)		(.21)					

Note: All samples include individuals between 25 and 59 years old who are currently working in non-agricultural industries.
[1]In the travel survey, the variable indicates whether there are children in the household. In the 2015 Census, the variable indicates whether having any biological children, and is only reported by women age 16 and above.
[2]In the mortgage sample, commute distance is the linear distance between home address and work address. In the travel survey sample, commute distance is the linear distance between the centroid of home Transportation Analysis Zone (TAZ) and that of the work TAZ. Commute distance is assumed to be 1 kilometer if the person lives and works in the same TAZ. In the 2015 Census, commute distance is the linear distance between the centroid of home district/township and that of the work district/township. Commute distance is assumed to be 1 kilometer if the person lives and works in the same district/township.

Table A.2: Gender Commute Gap in Various Data Sets

	mortgage sample ln commute dist. from		Beijing household travel survey		2015 census Beijing		2015 census nationwide	
	current home	new home	ln dist.	ln time	ln dist.	ln time	ln dist.	ln time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
= 1 if male	0.135	0.121	0.266	0.136	0.111	0.037	0.034	0.085
	(0.004)	(0.004)	(0.015)	(0.010)	(0.027)	(0.012)	(0.004)	(0.003)
N	247,979	247,979	54,820	57,871	24,590	25,076	745,374	909,193

Note: All samples include non-agricultural workers age between 25 and 59. All models controls for age bin fixed effects and detailed education attainment fixed effects. Standard errors are clustered at the community level in Columns 1 and 2; they are clustered at the TAZ level in Columns 3 and 4; They are clustered at the township level in Columns 5 to 8.

Table A.3: Commute in Other Household Arrangements

data:	mortgage sample		travel survey sample			
dep var:	log comm. dist.		log comm. dist.		log comm. time	
sample:	men	women	all	married	all	married
	(1)	(2)	(3)	(4)	(5)	(6)
= 1 if spouse employed	0.041	0.125				
	(0.009)	(0.011)				
ln monthly income	0.021	0.021				
	(0.002)	(0.002)				
= 1 if male			0.276	0.210	0.145	0.095
			(0.015)	(0.021)	(0.010)	(0.015)
male×single			-0.127		-0.100	
			(0.055)		(0.038)	
male×has children				0.111		0.083
				(0.026)		(0.019)
= 1 if single			-0.066		0.017	
			(0.043)		(0.030)	
= 1 if has children				-0.085		-0.081
				(0.025)		(0.018)
work district FE	X	X				
age bin FE	X	X	X	X	X	X
education FE	X	X	X	X	X	X
N	149959	132866	56454	52503	59894	55894

Note: The sample in Columns 1 and 2 includes married individuals from the mortgage sample regardless of spouse's employment status. Column 1 includes men, Column 2 includes women. Standard errors are clustered at the community level. The sample in Columns 3 to 6 includes working individuals from the Travel Survey. Columns 3 and 5 include both married and single individuals. Columns 4 and 6 include married individuals. "Has children" indicates whether there are children in the household. Standard errors in Columns 3 to 6 are clustered at the TAZ level.

B Estimation Procedure

The first step of our two-step estimation procedure is a maximum likelihood estimator, which returns estimates of the heterogeneous parameters θ_λ and the vector of mean indirect utilities δ_c. For any θ_λ, we use a contraction mapping to solve the vector of mean indirect utilities δ_c that forces the market shares predicted by the model to match those observed in the data.

$$\delta_c^{d+1} = \delta_c^d + \ln S_c - \ln s_c(\delta_c^d, \theta_\lambda), \tag{B.1}$$

where S_c is observed market share of community c and s_c is the market share predicted by δ_c^d and θ_λ in iteration d.

Using this contraction mapping algorithm, we can efficiently solve the vector $\hat{\delta}$ even when we have a large number of communities. Consequently, the likelihood function becomes $l(\delta, \theta_\lambda) = l(\hat{\delta}(\theta_\lambda), \theta_\lambda)$. This allows us to dramatically reduce the computational burden in the first step of the estimation because it avoids the search of free parameters δ.

As pointed out by McFadden (1978), we can estimate the model using a subsample of the alternatives not selected by the household. This simplifies the estimation in a situation with many alternatives. Let M_C denote the full set of communities in the choice set. We construct a subset M_c^i that contains the household's chosen house and a random sample of 19 communities from the remaining communities in M_C. Specifically, we randomly select 19 communities from all communities that had at least one unit sold in the three years around the time when the mortgage was taken out.

Given the sampling method, the probability that household i chooses community c can be re-written as

$$Prob_c^i = \frac{(C+1)}{N} \frac{\exp(\delta_c + \lambda_c^i)}{\sum_{j \in M_C^i} \exp(\delta_j + \lambda_j^i)}$$

where N is the total number of communities in the sample and $C = 19$ is the number of not chosen alternatives sampled for each household. The sum is now taken over only those alternatives in the subset M_C^i sampled for household i.

The random sample also leads to an adjustment in the calculation of predicted market share s_c, i.e., the predicted number of households that choose a community c. The reason is that the sampling procedure ensures that each household's actual choice is included in the subset of alternatives when calculating the choice probabilities, so the calculation of market share needs to be corrected for this oversampling. The adjusted market share is:

$$s_c(\delta^d, \theta_\lambda) = \sum_{i \in D} Prob_c^i + \frac{(N-1)}{C} \sum_{i \notin D, c \in M_C^i} Prob_c^i \tag{B.2}$$

where D contains the households that actually chooses community c, i.e., $I_c^i = 1$. The first term captures the contribution to the market share from households who actually chose community c, and the second

term considers the contribution of other households in the sample who could have chosen community c but did not.

C Additional Robustness Checks

C.1 Imputation of transportation mode

The mortgage data do not tell us which mode of transportation one uses for commute. We impute each individual's mode choice by fitting a discrete choice model using the Household Travel Survey, from which we observe respondents' mode choices. Specifically, we estimate a logit model where the outcome variable is an indicator for whether the commute is by car. Explanatory variables including demographic characteristics, household income, commuting distance, access to subway from home and workplace, and spousal characteristics. We interact each characteristic with binary gender indicators.

Table C.1 reports the marginal effects at the sample mean from three versions of logit estimations. Age has an inversed-U-shaped effect on the probability of driving. For both men and women, the age group between 35 and 44 are most likely to drive. This is probably due to the low car ownership among the younger groups, and fewer older people know how to drive, since private cars have only recently become popular among Chinese households. Not surprisingly, couples in households with higher income are more likely to drive. Husbands in households with an annual income above 300,000 yuan are 10 percentage points (p.p.) more likely to drive than those in households with an annual income less than 50,000 yuan, while wives are about 20 p.p. more likely. Individuals with a college degree are more likely to drive even conditional on household income. Having a college degree has a particularly high marginal effect on driving for women. Individuals who live farther away from their workplaces are more likely to drive. If commute distance is more than 15 km, men are 25 p.p. more likely and women are 26 p.p. more likely to drive compared with commute distance that is below 1 kilometer, in which case most choose to walk or bike.

Model 2 adds measures of access to the subway from home and workplace (between the centroids of the corresponding TAZs). Being close (less than 0.5 kilometers) to a subway station is strongly associated with less car use. Model 3 further adds spousal characteristics. Having a college-educated spouse is positively associated with one's own probability of using car for commute. If the spouse's commute is long, one's own probability of commuting by car is low. This is probably because most households in Beijing have at most one car.

We construct the same set of individual and household characteristics in the mortgage sample. Using estimated marginal effects from the Travel Survey, we predict the probabilities of driving for commute for each individual in the mortgage sample. In the Household Travel Survey, 34% of men commute by car, compared with 19% of women. According to the first model, the average predicted probability for men in the mortgage sample is 50%, for women it is 33%. The second model predicts a probability of 61% for men and 51% for women. The third model predicts 60% and 57%, respectively.

We calculate the predicted commute time as the sum of the multiplications between the predicted

probability of choosing either mode and the corresponding commute time.

Table C.1: Transportation Mode Prediction Models

	model 1		model 2		model 3	
dep var: = 1 commute by car	male	female	male	female	male	female
Age						
less than 34	0.061	-0.146	0.120	-0.110	0.215	-0.060
	(0.039)	(0.024)	(0.044)	(0.028)	(0.070)	(0.052)
35 - 44	0.124	-0.119	0.180	-0.084	0.254	-0.025
	(0.042)	(0.028)	(0.046)	(0.032)	(0.068)	(0.052)
45 - 54	0.095	-0.153	0.146	-0.124	0.243	-0.063
	(0.040)	(0.024)	(0.044)	(0.027)	(0.067)	(0.046)
55 and above	0.004	-0.163	0.055	-0.141	0.183	-0.112
	(0.035)	(0.016)	(0.040)	(0.020)	(0.071)	(0.035)
Education						
has college	0.005	0.080	0.025	0.097	0.003	0.043
	(0.005)	(0.008)	(0.005)	(0.008)	(0.009)	(0.011)
no college	-	-	-	-	-	-
Household annual income (yuan)						
$< 50,000$	-0.191	-0.150	-0.206	-0.166	-0.187	-0.167
	(0.017)	(0.022)	(0.016)	(0.020)	(0.020)	(0.024)
$[50,000; 100,000)$	-0.175	-0.106	-0.186	-0.123	-0.174	-0.128
	(0.024)	(0.031)	(0.023)	(0.029)	(0.031)	(0.037)
$[100,000; 150,000)$	-0.135	-0.076	-0.135	-0.083	-0.125	-0.080
	(0.020)	(0.031)	(0.020)	(0.030)	(0.030)	(0.038)
$[150,000; 200,000)$	-0.105	-0.035	-0.102	-0.041	-0.104	-0.037
	(0.022)	(0.036)	(0.022)	(0.035)	(0.031)	(0.044)
$[200,000; 250,000)$	-0.112	-0.029	-0.106	-0.032	-0.098	-0.029
	(0.021)	(0.039)	(0.022)	(0.038)	(0.032)	(0.047)
$[250,000; 300,000)$	-0.088	-0.007	-0.081	-0.007	-0.085	-0.020
	(0.026)	(0.043)	(0.027)	(0.043)	(0.036)	(0.050)
$[300,000; 500,000)$	-0.086	0.048	-0.080	0.039	-0.072	0.046
	(0.028)	(0.056)	(0.030)	(0.055)	(0.043)	(0.069)
$> 500,000$	-	-	-	-	-	-
Commuting distance						
< 1 km	-0.250	-0.264	-0.262	-0.271	-0.247	-0.289
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
$1 - 2.5$ km	-0.152	-0.168	-0.158	-0.173	-0.155	-0.183
	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)	(0.006)
$2.5 - 5$ km	-0.103	-0.112	-0.107	-0.115	-0.101	-0.124
	(0.005)	(0.007)	(0.005)	(0.006)	(0.008)	(0.008)
$5 - 10$ km	-0.052	-0.062	-0.047	-0.059	-0.039	-0.066
	(0.006)	(0.008)	(0.006)	(0.008)	(0.009)	(0.010)
$10 - 15$ km	-0.035	-0.034	-0.026	-0.027	-0.023	-0.016
	(0.07)	(0.010)	(0.007)	(0.010)	(0.011)	(0.013)
> 15 km	-	-	-	-	-	-

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cont'd	model 1		model 2		model 3	
	male	female	male	female	male	female
Access to subway						
Home dist to nearest subway stn						
less than 0.5 km			-0.032	-0.007	-0.038	0.014
			(0.006)	(0.009)	(0.010)	(0.013)
0.5 - 1 km			-0.002	0.025	-0.007	0.029
			(0.007)	(0.011)	(0.012)	(0.015)
1 - 2 km			0.011	0.046	0.012	0.044
			(0.009)	(0.013)	(0.013)	(0.017)
more than 2 km			-	-	-	-
Work dist to nearest subway stn						
less than 0.5 km			-0.126	-0.128	-0.135	-0.164
			(0.005)	(0.007)	(0.008)	(0.010)
0.5 - 1 km			-0.055	-0.062	-0.058	-0.083
			(0.007)	(0.009)	(0.010)	(0.011)
1 - 2 km			0.003	-0.033	-0.019	-0.067
			(0.009)	(0.011)	(0.013)	(0.013)
more than 2 km			-	-	-	-
Spousal characteristics						
spouse has college degree					0.030	0.044
					(0.009)	(0.011)
spouse's log commute dist					-0.006	-0.018
					(0.003)	(0.004)
predicted % use car (mortgage)	50	33	61	51	60	57

Note: The sample is from the 2015 Household Travel Survey. The dependent variable is an indicator whether the person drives or rides a car to work. All three models are estimated using a logit regression. Each coefficient is associated with a variable that is the interaction between the male or female indicator and the indicated characteristic. For example, the first number reported in the table is associated with the male indicator interacted with an binary variable indicating the less than 34 year old group. The constant is suppressed. Marginal effects at the sample mean are reported with robust standard errors in parentheses.

C.2 Robustness in the second-step estimation

Table C.2 shows robustness in the second-step estimation, whose main result is reported in Table 4. In all columns in Table C.2, we use δ_c from Model 2 and instrument log price per square meter. Across all columns, we gradually add community features and neighborhood amenities. Although not a formal test, these exercises shed light on the validity of the instrument. As first demonstrated in Altonji, Elder, and Taber (2005) and recently discussed in Oster (2019), if there is remaining endogeneity in log price that is not addressed by the instrument, adding these community and neighborhood characteristics, which are likely correlated with price, would have an impact on the coefficient associated with log price. Instead, the coefficient is stable across all columns. This is suggestive evidence that the instrumental variable has successfully isolated exogenous variation (Altongji, Elder, and Taber 2005; Oster, 2019).

Table C.2: House Choice Model - Second Stage Estimates Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln price per sqm	-4.051	-3.886	-4.289	-4.440	-4.571	-4.402	-4.624	-4.846	-4.471
	(0.252)	(0.330)	(0.317)	(0.320)	(0.434)	(0.311)	(0.394)	(0.644)	(0.992)
ln year of completion		0.841	0.634	0.617	0.618	0.614	0.642	0.643	0.641
		(0.288)	(0.202)	(0.195)	(0.199)	(0.192)	(0.197)	(0.199)	(0.193)
ln avg unit size (sqm)		-0.229	-0.765	-0.819	-0.835	-0.816	-0.860	-0.892	-0.832
		(0.216)	(0.209)	(0.196)	(0.204)	(0.195)	(0.206)	(0.232)	(0.278)
ln floor-to-area ratio		-0.042	-0.102	-0.088	-0.094	-0.085	-0.085	-0.088	-0.079
		(0.078)	(0.083)	(0.078)	(0.079)	(0.078)	(0.075)	(0.077)	(0.073)
ln green area ratio			0.060	0.051	0.050	0.048	0.069	0.063	0.062
			(0.082)	(0.085)	(0.085)	(0.087)	(0.095)	(0.094)	(0.091)
ln # of units			0.551	0.548	0.546	0.547	0.559	0.556	0.555
			(0.055)	(0.054)	(0.054)	(0.053)	(0.054)	(0.053)	(0.052)
ln management fee			0.145	0.146	0.146	0.145	0.152	0.154	0.146
			(0.033)	(0.035)	(0.035)	(0.034)	(0.035)	(0.037)	(0.034)
ln college ratio				0.672	0.672	0.651	0.835	0.840	0.577
				(0.560)	(0.561)	(0.550)	(0.510)	(0.506)	(0.666)
ln ratio w/ Beijing hukou				-0.476	-0.395	-0.442	-0.643	-0.523	-0.458
				(0.459)	(0.481)	(0.467)	(0.470)	(0.471)	(0.458)
ln dist. to subway station					-0.047			-0.074	-0.083
					(0.073)			(0.086)	(0.081)
ln # of bus stops					0.007			-0.028	-0.032
					(0.153)			(0.191)	(0.182)
ln inverse AQI						0.115		0.166	0.193
						(0.331)		(0.324)	(0.330)
ln # of key primary schl							-0.099	-0.080	-0.055
							(0.095)	(0.117)	(0.118)
ln # of key secondary schl							0.234	0.267	0.249
							(0.098)	(0.115)	(0.129)
ln dist to city center									0.157
									(0.265)
constant	39.000	35.224	38.768	40.744	42.044	40.309	42.533	44.895	40.542
	(2.550)	(4.670)	(4.120)	(3.765)	(5.239)	(3.767)	(4.542)	(7.655)	(12.169)
first-stage F-stat	913.42	984.95	831.54	660.71	446.24	646.51	419.07	216.02	89.86

Note: Each observation is a community. There are 5,279 communities in the sample. The dependent variable is δ_c from Model 2 in Table 3. Log price per square meter is instrumented. Standard errors account for flexible spatial correlation up to 5 kilometers.

C.3 Additional specification tests

Random coefficients

Our estimation allows for heterogeneous preferences for community and neighborhood characteristics by interacting these characteristics with household features. This approach does not capture unobserved heterogeneity in preference. To gauge the importance of the unobserved preference heterogeneity,

we allow for random coefficients on the key parameters: log price, the difference in log commute distances, and the average of log commute distances. Column 1 of Table C.3 reports the estimation results. The variances of the coefficients are in general small. The means of the coefficients remain unchanged.

Heterogeneity in access to transit

In the baseline specification, we use the difference in log commute *distance*. Arguably, people care more about commute *time* than distance. Therefore, we present robustness evidence in Table 5 where commute time is used.

The conversion of commute distance to commute time varies by the access to different modes of transportation. Therefore, an alternative way to mitigate the mis-measurement of commute cost is to account for the heterogeneity in access to public transit. On top of the baseline specification, we interact differences in commute distance with the log distance to the nearest subway station and the log number of bus stops in the neighborhood, both demeaned within the sample. Column 2 of Table C.3 shows that the main coefficient of interest is essentially unchanged.

Dropping average commute distance

In the main paper, we caution that the average commute distance of the household is likely correlated with distance to downtown and can be endogenous to amenities. We focus on the main variable of interest — the gap in commute distance between the husband and the wife — such that it is likely uncorrelated with the average commute distance. However, the empirical correlation between the two variables is not exactly zero in our sample. We can gauge how much bias the finite sample correlation could have resulted by dropping the average commute distance from the regression. Column 3 of Table C.3 shows that the coefficient associated with the difference in gender commute gap is somewhat larger at 0.12. Our conclusion remains unchanged.

Varying the choice set

In the baseline, we restrict the choice set to 20 communities, including the one that is actually chosen. Using a subset of communities to form the choice set is primarily for computational convenience, and the choice of 20 communities is arbitrary.

In Columns 4 and 5 of Table C.3, we show that results are similar when the choice set is expanded to 30 or 40 randomly chosen communities (the one that is actually chosen is always included).

Housing as investment

Throughout the paper we assume that after a household buys a new home, it will move there. In fact, households may buy homes as a means of investment. If it is the household's second home, it may not actually move there, rendering our analysis irrelevant.

To rule out this possibility, we restrict the sample to the fist-time home buyers. The mortgage sample reports whether the household owns or rents the current home. We drop about 13% of the households that are already home owners.

Column 6 of Table C.3 reports the estimation results from the sample of first-time homeowners. The results are again very similar to the baseline.

Table C.3: Additional Specification Checks

	(1) random coeff.	(2) hetero. in access to transit	(3) dropping avg. dist.	(4) 30 choices	(5) 40 choices	(6) 1st-time owner
			first-step estimations			
diff. in ln comm. dist.	0.0794	0.0845	0.1233	0.0811	0.0786	0.0862
(husband - wife)	(0.0012)	(0.0009)	(0.0076)	(0.0065)	(0.0062)	(0.0074)
avg. ln comm. dist	-1.1140	-1.1132		-1.1958	-1.1647	-1.2924
	(0.0021)	(0.0021)		(0.0130)	(0.0126)	(0.0145)
ln dist. to current home	-1.0708	-1.0698	-1.4689	-1.1094	-1.1050	-1.1389
	(0.0017)	(0.0017)	(0.0005)	(0.0070)	(0.0068)	(0.0079)
ln p X						
ln hhd. income	0.2546	0.2857	0.2909	0.2939	0.2901	0.2705
	(0.0045)	(0.0067)	(0.0208)	(0.0218)	(0.0214)	(0.0242)
husband age	1.2525	1.3475	1.0689	1.5414	1.4729	1.6166
	(0.0171)	(0.0219)	(0.0950)	(0.0990)	(0.0962)	(0.1142)
diff. in ln comm. dist. X						
ln dist. to subway stn.		0.0037				
		(0.0001)				
ln # of bus stops		-0.0105				
		(0.0001)				
s.e. of random coeff.						
diff. in ln comm. dist.	0.0004					
(husband - wife)	(0.0001)					
avg. ln comm. dist.	0.0453					
	(0.0149)					
ln p	0.0276					
	(0.0000)					
			second-step estimations			
ln p	-4.847	-4.840	-3.601	-4.886	-4.701	-5.304
	(0.644)	(0.644)	(0.561)	(0.664)	(0.649)	(0.690)
F-stat for IV power	216	216	216	216	216	213
# of households	125,466	125,466	125,466	125,466	125,466	108,812
# of unique communities	5,279	5,279	5,279	5,279	5,279	5,192
# of observations	2,509,320	2,509,320	2,509,320	3,763,980	5,018,640	2,176,240

Note: All models are estimated using the two-step procedure. Column 1 allows for random coefficients on key explanatory variables. Column 2 adds the interactive terms between the gender gap in log commute distance with demeaned log distance to the nearest subway station and demeaned log number of bus stops in the neighborhood. Column 3 drops the average log commute distance between the husband and the wife. Columns 4 and 5 expand the randomly selected choice set to 30 and 40 communities, respectively. Column 6 restricts the sample to households that are first-time homeowners. Standard errors account for flexible spatial correlation up to 5 kilometers.

C.4 Conditional logit estimation

Instead of the two-step approach, the indirect utility model described in Eqn (10) can also be estimated using the conditional logit. We use the same set of control variables as in Model 2 of Tables 3 and 4. To instrument for log price per square meter, we run the first-stage regression and plug the predicted log price in the second-stage regression. This "hand-made" two-stage estimation introduces non-random error. Therefore, we obtain standard errors by bootstrapping the estimation 500 times (including the original estimation). Column 1 of Table C.4 shows that the conditional logit estimation yields similar results as in the two-step estimation. β_d/β_{0p} is about -0.02. Column 2 repeats the estimation with measures in commute *time* instead of commute distance. The results are similar with those in Table 5.

In results not reported here, we estimate various versions of the conditional logit model with varying controls of the community and neighborhood characteristics, as well as their interactive terms with household characteristics. β_d and β_{0p} are stable across all specifications. The coefficient associated with the average log commute distance, β_a, is also stable at around -1.2. If there is strong correlation between the average log commute distance and unobserved community and neighborhood characteristics that could bias the estimated β_a, the gradual inclusion of the *observed* endogenous community and neighborhood characteristics would have resulted in substantive changes in the estimated coefficient. The stability of the coefficient lends us confidence that the β_a is also credibly identified.

According to our estimates, β_d/β_a is about -0.065: This suggests one log point increase in the husband's commute distance relative to the wife's is equivalent to a 0.065 log point increase in the average commute distance. β_{0p}/β_a is about 3, suggesting that households are more sensitive to changes in prices than in commute distances. This is consistent with the empirical pattern in the data. People seem to be willing to live farther away from the city center for relatively small price discounts — in our sample, the interquartile difference in price per square meter is about 40%, while that in average commute is almost 350%.

C.5 Measurement error in travel time

One concern with commute time is that it is likely measured with error. The measurements error come from two sources. First, the imputation process introduces measurement errors. Second, we use the 2015 Travel Survey to impute commute time, even if the imputation itself is free of measurement error, the 2015 speed may be an imperfect proxy for the traffic condition households actually face.

The usual approach to address measurement error problem, if we assume the measurement error is classical, is to find another measure of the same variable. The other measure serves as a valid instrument as long as its measurement error is also classical and is uncorrelated with that of the original variable.

We construct an alternative measure of commute time using Baidu Maps, a popular digital map website and trip planner. Baidu Maps provides an developer interface at https://lbsyun.baidu.com/, which we use to calculate commute time between pairs of home-work addresses in the mortgage sample. We randomly select 30,000 home-work address pairs from our sample (including commutes for both men and women, and from work to both actual and choice home locations), and calculate commute

time using two kinds of mode choices: public transit or private car. Public transit includes buses and subways. We choose to conduct 30,000 queries mostly in order to save time (the whole sample requires half a million queries) while maintaining a large-enough sample to accurately impute the commute time for the remaining commutes. Queries can be made based on current traffic condition or predicted traffic condition in the next week. We use the predicted traffic condition in the next Monday morning, assuming departure time at 7AM. We sent the queries in the first week of July, 2020.

Baidu Maps typically returns a few route options. For trips using public transit, the options include those with the shortest time, shortest walking distance, fewest interchanges, or avoiding the subway (which is more expensive than buses). For automobile trips, the options include those with the shortest time, the shortest distance, or avoiding highways. For each mode of transportation, we use the default option, which is typically the one with the shortest travel time.

Commute time by public transit includes walking time to the bus stop or subway station, as well as expected wait time. Commute time by private car is driving time only. We add 5 minutes on each end of a car trip to account for the access time to one's car. For commutes with linear distances below 1 kilometer, we also calculate the time needed if one chooses to ride a bike to work, assuming the bike route is the same as the route for driving and imposing an average speed of cycling in the city as 7 kilometers per hour. We assume there is no access time to one's bike. And if bike turns out to be the most time-saving option, we assume that the person chooses to ride a bike.

With commute time calculated for 30,000 commutes, we estimate Eqn (11) and impute the time needed for the remaining commutes in the sample. We assign the mode of transport for each individual based on the mode prediction model using a random half of the Travel Survey sample, thus breaking the correlation in measurement error in predicted transportation mode.

We estimate the conditional logit model where the average of log commute time and the difference in log commute time, constructed from the Travel Survey, are instrumented by their counterparts imputed from Baidu Maps. Column 3 of Table C.4 reports the results of the conditional logit estimation with all three variables – gender difference in log commute time, average of log commute time, and log price per square meter – instrumented. Consistent with the attenuation bias due to classical measurement error, coefficients associated with commute time measures in Column 3 are larger in magnitude than those in Column 2, where commute time is not instrumented.

Table C.4: Conditional Logit Estimations

	(1)	(2)	(3)
diff. in ln commute dist.	0.078		
(husband - wife)	(0.006)		
avg. ln commute dist.	-1.199		
	(0.014)		
diff. in ln commute time		0.118	0.182
(husband - wife)		(0.009)	(0.011)
avg. ln commute time		-2.210	-2.610
		(0.024)	(0.031)
ln price per sqm	-3.717	-3.372	-3.767
	(0.149)	(0.148)	(0.149)
instrumented			
ln price per sqm	X	X	X
diff. in ln commute time			X
avg. ln commute time			X

Note: Each model is estimated using conditional logit. All models also include the same set of variables as in Column 2 of Table 3 and Table 4, whose coefficients are suppressed. In all models, log price per square meter is instrumented using the same instrumental variable as in Table 4. Commute time for the chosen and alternative homes are imputed by fitting a model of travel time using the household travel survey. In Column 3, average log commute time and the gender difference in log commute time are instrumented using the counterparts constructed from imputed commute time using predicted travel time from Baidu Maps. See text for detail. Standard errors are obtained by bootstrapping 500 times.

D Model Details

D.1 Model solution and proofs of propositions

Solving household's problem. The household's problem is as follows. Conditional on the work locations of the couple, the household solves the resource allocation problem by choosing the commute time, home production time, leisure time, and consumption level for the husband and the wife (t_m, t_f, l_m, l_f, L_m, L_f, c_m, and c_f):

$$\max_{t_m,t_f,l_m,l_f,L_m,L_f,c_m,c_f} \log c_m + \mu \log c_f + (1+\mu)\alpha_Q \log Q + \alpha_m \log L_m + \mu\alpha_f \log L_f \tag{D.1}$$

$$\begin{aligned} s.t. \quad & t_i + l_i + L_i = T \quad \text{for}, i \in \{m, f\} \\ & w_m + w_f = c_m + c_f + bD \\ & Q = (\gamma l_f^\rho + l_m^\rho)^{1/\rho} \\ & t_m + t_f = D \\ & t_i \geq 0, \quad l_i \geq 0, \quad L_i \geq 0 \quad \text{for } i \in \{m, f\} \end{aligned}$$

The first order conditions with respect to c_m and c_f are:

$$\begin{aligned}
\frac{1}{c_m} &= \lambda_c \\
\mu \frac{1}{c_f} &= \lambda_c \\
\frac{c_m}{c_f} &= \frac{1}{\mu}
\end{aligned} \tag{D.2}$$

Given household's income $w_m + w_f$, the couple splits the consumption based on Eqn (D.2). Therefore, we can solve c_m and c_f:

$$\begin{aligned}
c_m &= \frac{1}{1+\mu}(w_m + w_f - bD) \\
c_f &= \frac{\mu}{1+\mu}(w_m + w_f - bD)
\end{aligned}$$

Plugging the solution back into the household maximization problem, we have the following Lagrange equation:

$$\begin{aligned}
\max_{h_m, h_f, t_m, l_m, l_f, L_m, L_f} \; & \log \frac{1}{1+\mu}(w_m + w_f - bD) + \mu \log \frac{\mu}{1+\mu}(w_m + w_f - bD) \\
& + (1+\mu)\alpha_Q \rho \log(\gamma l_f^\rho + l_m^\rho) + \alpha_m \log L_m + \mu \alpha_f \log L_f \\
& + \lambda_m (T - l_m - L_m - t_m) + \lambda_f (T - l_m - L_m - D + t_m)
\end{aligned} \tag{D.3}$$

Here we replace t_f with $D - t_m$ and replace L_i with $T - l_i - t_i$.

Taking the first order condition with respect to l_m, l_f and t_m, we have

$$l_m : \quad \frac{(1+\mu)\alpha_Q l_m^{\rho-1}}{\gamma l_f^\rho + l_m^\rho} = \lambda_m \tag{D.4}$$

$$l_f : \quad \frac{(1+\mu)\alpha_Q \gamma l_f^{\rho-1}}{\gamma l_f^\rho + l_m^\rho} = \lambda_f \tag{D.5}$$

$$L_m : \quad \frac{\alpha_m}{L_m} = \lambda_m \tag{D.6}$$

$$L_f : \quad \mu \frac{\alpha_f}{L_f} = \lambda_f \tag{D.7}$$

$$t_m : \quad \lambda_m = \lambda_f \tag{D.8}$$

From Eqns (D.4) and (D.5), we have

$$\frac{l_m}{l_f} = (\gamma)^{\frac{1}{\rho-1}} \tag{D.9}$$

From Eqns (D.6) and (D.7), we have

$$\frac{L_m}{L_f} = \frac{\alpha_m}{\mu\alpha_f} \tag{D.10}$$

Plugging Eqns (D.9) and (D.10) into the time constraint, we get

$$\begin{aligned} l_m + l_f + L_m + L_f &= 2T - D \\ (\gamma^{\frac{1}{1-\rho}} + 1)l_m + (1 + \frac{\mu\alpha_f}{\alpha_m})L_m &= 2T - D \end{aligned} \tag{D.11}$$

Plugging Eqns (D.6) and (D.9) into Eqn (D.4), we get

$$\begin{aligned} \frac{(1+\mu)\alpha_Q}{(\gamma^{\frac{2-\rho}{1-\rho}} + 1)l_m} &= \frac{\alpha_m}{L_m} \\ \alpha_m(\gamma^{\frac{2-\rho}{1-\rho}} + 1)l_m - (1+\mu)\alpha_Q L_m &= 0 \end{aligned} \tag{D.12}$$

Solving Eqns (D.11) and (D.12), we get the solution of l_m and L_m:

$$l_m = \frac{(2T-D)(1+\mu)\alpha_Q}{(\gamma^{\frac{1}{1-\rho}} + 1)(1+\mu)\alpha_Q + \alpha_m(\gamma^{\frac{2-\rho}{1-\rho}} + 1)(1 + \frac{\mu\alpha_f}{\alpha_m})} \tag{D.13}$$

$$L_m = \frac{(2T-D)\alpha_m(\gamma^{\frac{2-\rho}{1-\rho}} + 1)}{(\gamma^{\frac{1}{1-\rho}} + 1)(1+\mu)\alpha_Q + \alpha_m(\gamma^{\frac{2-\rho}{1-\rho}} + 1)(1 + \frac{\mu\alpha_f}{\alpha_m})} \tag{D.14}$$

From the above two equations and the time constraint, we get

$$t_m = T - \frac{(2T-D)((1+\mu)\alpha_Q + \alpha_m(\gamma^{\frac{2-\rho}{1-\rho}} + 1))}{(\gamma^{\frac{1}{1-\rho}} + 1)(1+\mu)\alpha_Q + \alpha_m(\gamma^{\frac{2-\rho}{1-\rho}} + 1)(1 + \frac{\mu\alpha_f}{\alpha_m})} \tag{D.15}$$

Proof of Proposition 1. Proof: Based on Eqn (D.15), t_m increases with α_Q if and only if:

$$\frac{(1+\mu)}{(\gamma^{\frac{1}{1-\rho}} + 1)(1+\mu)} < \frac{\alpha_m(\gamma^{\frac{2-\rho}{1-\rho}} + 1)}{\alpha_m(\gamma^{\frac{2-\rho}{1-\rho}} + 1)(1 + \frac{\mu\alpha_f}{\alpha_m})}$$

This is equivalent to

$$\gamma^{\frac{1}{1-\rho}} > \frac{\mu\alpha_f}{\alpha_m}.$$

Proof of Corollary 1. Proof: Eqn (D.9) says $l_m/l_f = (\gamma)^{1/(\rho-1)}$. Because $\rho < 1$, $\gamma < 1$ is a sufficient condition for $l_m > l_f$; $\gamma > 1$ is a sufficient condition for $l_m < l_f$.

Proof of Proposition 2. Proof: We can re-arrange Eqn (D.15) as a function of μ.

$$t_m = T - \frac{\alpha_Q \mu + (\alpha_Q + (\gamma^{\frac{2-\rho}{1-\rho}} + 1)\alpha_m)}{((\gamma^{\frac{1}{1-\rho}} + 1)\alpha_Q + (\gamma^{\frac{2-\rho}{1-\rho}} + 1)\alpha_f)\mu + ((\gamma^{\frac{1}{1-\rho}} + 1)\alpha_Q + (\gamma^{\frac{2-\rho}{1-\rho}} + 1)\alpha_m)}$$

t_m increases with μ if and only if

$$\frac{\alpha_Q}{(\gamma^{\frac{1}{1-\rho}} + 1)\alpha_Q + (\gamma^{\frac{2-\rho}{1-\rho}} + 1)\alpha_f} < \frac{\alpha_Q + (\gamma^{\frac{2-\rho}{1-\rho}} + 1)\alpha_m}{(\gamma^{\frac{1}{1-\rho}} + 1)\alpha_Q + (\gamma^{\frac{2-\rho}{1-\rho}} + 1)\alpha_m}$$

This is equivalent to the following

$$\gamma^{\frac{1}{1-\rho}}(\gamma^{\frac{2-\rho}{1-\rho}} + 1)\alpha_m\alpha_Q + (\gamma^{\frac{2-\rho}{1-\rho}} + 1)\alpha_f\alpha_Q + (\gamma^{\frac{2-\rho}{1-\rho}} + 1)^2\alpha_m\alpha_f > 0$$

Because the above inequality always holds, we prove the proposition.

D.2 An extended model of home-location choice with flexible work hours

In this extended model, we allow the husband and the wife to choose their work hours h_i. The utility function of the household is

$$U_m + \mu U_f, \tag{D.16}$$
$$\text{where } U_i = \log c_i + \alpha_Q \log Q + \alpha_i \log L_i + \alpha_t t_i^2 \quad \text{for } i \in \{m, f\}$$

where μ is the Pareto weight of the wife. α_Q captures the preference on public good Q. α_i captures individual i's idiosyncratic preference for leisure L_i. α_t captures the physic cost of commuting which is not captured by the monetary or time costs.[2]

Household public good Q is produced by husband's time l_m and wife's time l_f:

$$Q = (\gamma l_f^\rho + l_m^\rho)^{1/\rho} \tag{D.17}$$

Individual time inputs are aggregated to household public good via a CES production function. γ captures the time efficiency of wife relative to that of husband. ρ describes the elasticity of substitution between wife's time and husband's time.

Time constraint for individual i is

$$T = h_i + t_i + l_i + L_i \tag{D.18}$$

Total time T is divided into work time h_i, commute time t_i, time spent on producing household public good l_i, and leisure L_i.

[2]We add this term to make sure that we have an interior solution. We adopt a quadratic functional form because it predicts that, when the husband and the wife are exactly the same, they prefer to live on the mid point of the two workplaces.

Household budget constraint is

$$w_m h_m + w_f h_f = c_m + c_f + bt_m + bt_f \tag{D.19}$$

where w_i is the wage rate of couple i, and b is the monetary cost of commuting.

Household's problem is the following, conditional on work locations of the couple, households solve resource allocation problems by choosing labor supply, commute time, home production time, leisure, and consumption level for the husband and wife (h_m, h_f, t_m, t_f, l_m, l_f, L_m, L_f, c_m, and c_f):

$$\max_{h_m,h_f,t_m,t_f,l_m,l_f,L_m,L_f,c_m,c_f} \log c_m + \mu \log c_f + (1+\mu)\alpha_Q \log Q + \alpha_m \log L_m + \mu\alpha_f \log L_f - \alpha_t t_m^2 - \mu\alpha_t t_f^2 \tag{D.20}$$

$$\begin{aligned} s.t. \quad & h_i + t_i + l_i + L_i = T \quad \text{for, } i \in \{m, f\} \\ & w_m h_m + w_f h_f = c_m + c_f + bD \\ & Q = (\gamma l_f^\rho + l_m^\rho)^{1/\rho} \\ & t_m + t_f = D \\ & \quad t_i \geq 0, \quad l_i \geq 0, \quad L_i \geq 0 \quad \text{for } i \in \{m, f\} \end{aligned}$$

The solution maximizes household utility, subject to time constraint (Eqn (D.18)), budget constraint (Eqn (D.19)), and public good production technology (Eqn (D.17)). Below, we consider the interior solution where $h_m > 0$ and $h_f > 0$, as the trade-off between husband's and wife's commute time only matters when both are working.

The first order conditions with respect to c_m and c_f are:

$$\begin{aligned} \frac{1}{c_m} &= \lambda_c \\ \mu\frac{1}{c_f} &= \lambda_c \\ \frac{c_m}{c_f} &= \frac{1}{\mu} \end{aligned} \tag{D.21}$$

Therefore, given household's income $w_m h_m + w_f h_f$, the couple splits the consumption based on Eqn (D.21). Therefore, we can solve c_m and c_f:

$$\begin{aligned} c_m &= \frac{1}{1+\mu}(w_m h_m + w_f h_f - bD) \\ c_f &= \frac{\mu}{1+\mu}(w_m h_m + w_f h_f - bD) \end{aligned}$$

Plug the solution back to the household maximization problem, we have the following Lagrange equa-

tion:

$$\max_{h_m,h_f,t_m,l_m,l_f,L_m,L_f} \log \frac{1}{1+\mu}(w_m h_m + w_f h_f - bD) + \mu \log \frac{\mu}{1+\mu}(w_m h_m + w_f h_f - bD) \tag{D.22}$$
$$+ (1+\mu)\alpha_Q \rho \log(\gamma l_f^\rho + l_m^\rho) + \alpha_m \log L_m + \mu \alpha_f \log L_f - \alpha_t (t_m^2 + \mu(D - t_m)^2)$$
$$+ \lambda_m (T - h_m - l_m - L_m - t_m) + \lambda_f (T - h_f - l_f - L_f - D + t_m)$$

Here we replace t_f by $D - t_m$.

Taking the first order condition with respect to $h_m, h_f, l_m, l_f, L_m, L_f$, and t_m, we have

$$h_m: \quad \frac{w_m(1+\mu)}{w_m h_m + w_f h_f - bD} - \lambda_m = 0 \tag{D.23}$$

$$h_f: \quad \frac{w_f(1+\mu)}{w_m h_m + w_f h_f - bD} - \lambda_f = 0 \tag{D.24}$$

$$l_m: \quad \frac{(1+\mu)\alpha_Q l_m^{\rho-1}}{\gamma l_f^\rho + l_m^\rho} - \lambda_m = 0 \tag{D.25}$$

$$l_f: \quad \frac{(1+\mu)\alpha_Q \gamma l_f^{\rho-1}}{\gamma l_f^\rho + l_m^\rho} - \lambda_f = 0 \tag{D.26}$$

$$L_m: \quad \frac{\alpha_m}{L_m} - \lambda_m = 0 \tag{D.27}$$

$$L_f: \quad \mu \frac{\alpha_f}{L_f} - \lambda_f = 0 \tag{D.28}$$

$$t_m: \quad -\lambda_m + \lambda_f - (2\alpha_t t_m - 2\alpha_t \mu (D - t_m)) = 0 \tag{D.29}$$

We have the following proposition:

Proposition 3 *When husband's wage rate w_m increases, his commute time t_m decreases.*

Proof: When w_m increases, λ_m increases according to Eqn (D.23) and λ_f decreases according to Eqn (D.24). Based on Eqn (D.29), t_m decreases.

Proposition 4 *When wife's bargaining power μ increases, husband's commute time t_m increases.*

Proof: When μ increases from μ^{old} to μ^{new}, we have

$$\frac{\lambda_i^{new}}{\lambda_i^{old}} < \frac{\mu^{new}}{\mu^{old}} \quad for i \in \{m, f\}$$

Suppose we increase λ_m and λ_f by $\frac{\mu^{new}}{\mu^{old}}$, Eqns (D.23) to (D.27) will become negative, while Eqn (D.28) remains unchanged. Therefore, we have to reduce λ_m and λ_f. From Eqns (D.23) and (D.24), we have

$$\frac{\lambda_m}{\lambda_f} = \frac{w_m}{w_f}$$

According to Eqn (D.29), we have

$$(1-\frac{w_f}{w_m})\lambda_m^{old} < 2\alpha_t(D-t_m)\mu^{old}$$
$$(1-\frac{w_f}{w_m})\lambda_m^{old}(\frac{\lambda_m^{new}}{\lambda_m^{old}}-1) < 2\alpha_t(D-t_m)\mu^{old}(\frac{\mu^{new}}{\mu^{old}}-1)$$
$$(1-\frac{w_f}{w_m})\lambda_m^{new} - 2\alpha_t\mu^{new}(D-t_m) < (1-\frac{w_f}{w_m})\lambda_m^{old} - 2\alpha_t\mu^{old}(D-t_m)$$

Since $2\alpha_t t_m = -[(1-\frac{w_f}{w_m})\lambda_m - 2\alpha_t\mu(D-t_m)]$, t_m increases.

Proposition 5 *When α_Q increases, t_m decreases.*

Proof: When α_Q increases, λ_m and λ_f increase, according to Eqn (D.25) and (D.26). Based on Eqn (D.29),

$$2\alpha_t(1+\mu)t_m = -(1-\frac{w_f}{w_m})\lambda_m + 2\alpha_t\mu D$$

As a result, t_m decreases.

E Additional Results

Table E.1: Gender Commute Gap in the United States

	(1)	(2)	(3)	(4)
	dep var: log commute time			
= 1 if male	0.103	0.112	0.106	0.108
	(0.001)	(0.001)	(0.001)	(0.001)
demographic controls		X	X	X
geographic controls			X	X
modes of transportation				X

Note: The data is from the 2017 American Community Survey, which represents 1% of the U.S. population. The sample includes individuals between 25 and 64 years old, not in group quarters, work at least half time (more than 20 weeks last year and more than 20 hours in a typical week), and commute to work (excluding those who work from home). Demographic controls include four age bins, whether having children under 6, marital status, and a set of detailed education attainment indicators. Geographic controls include the metropolitan statistical area (MSA) of residence. A state's rural area is also included as one "MSA." Variables on the mode of transportation include a list of indicators for major transportation modes.

Table E.2: Correlation Coefficients between Commute Distance and Community Characteristics

	diff in ln comm. dist. (husband - wife)	avg. ln comm. dist.
avg. ln comm. dist.	-.047	1
ln price per sqm	-.003	-.102
ln dist. to current home	-.050	.461
ln dist. to city center	-.001	.145
ln year of completion	-.016	.189
ln avg. unit size (sqm)	-.014	.044
ln floor-to-area ratio	.015	-.065
ln green-area ratio	-.014	.059
ln # of buildings	-.007	.051
ln management fee (yuan/sqm)	-.018	.103
college ratio in neighborhood	.001	-.112
ratio w/ Beijing hukou in neighborhood	.025	-.123
ln dist. to the nearest subway station	.013	-.009
ln # of bus stops in neighborhood	.035	-.135
ln inverse air quality index (AQI)	-.023	.172
ln # of key elementary schools in neighborhood	.018	-.208
ln # of key middle and high schools in neighborhood	.023	-.197

Note: Correlation coefficients between community characteristics or neighborhood amenities and average of or difference in log commute distances.

Table E.3: Suppressed Coefficients from Table 3, Column 4

	dist. to subway station	# of bus stops	ln inv. AQI	# of key elementary schools	# of key middle & high schools	share of college graduates	share with Beijing hukou
×husband age	0.0379	0.0469	0.0937	0.0018	0.0974	0.0301	-0.0943
	(0.0007)	(0.0000)	(0.0030)	(0.0002)	(0.0000)	(0.0014)	(0.0035)
×ln hhd income	0.2275	-0.0290	-0.6024	0.0835	0.0322	0.0977	0.0969
	(0.0038)	(0.0000)	(0.0068)	(0.0000)	(0.0013)	(0.0087)	(0.0011)

Note: This table reports coefficients suppressed from Table 3, Column 4. Each pair of cells report the coefficient associated with the interactive term between the community characteristic or neighborhood amenity and the household characteristic and the associated standard error (in parentheses).

Table E.4: Home Location Choice and Gender Gap in Commuting, by Demographic Groups

	(1)	(2)	(3)	(4)	(5)	(6)
group	college	no college	< 35	$[35, 44]$	$[45, 54]$	$[55, 64]$
	dep var: ln commute dist btw work and new home					
= 1 if male	0.102	0.130	0.106	0.144	0.098	0.078
	(0.004)	(0.005)	(0.004)	(0.007)	(0.011)	(0.044)
Fixed effects						
age bin	X	X				
detailed edu attainment	X	X	X	X	X	X
home district	X	X	X	X	X	X
N of obs	146,244	151,919	184,211	79,036	31,659	3,257

Note: Each column corresponds to a subsample of the mortgage sample. Robust standard errors in parentheses.

F Descriptions of Data Sources

The administrative records of mortgage data are provided by an anonymous mortgage lender in Beijing. We are not allowed to reveal its identity.

Beijing Household Travel Survey is conducted by the Beijing Transportation Institute (BTI). This survey is conducted every year since 2005. Once every five years, the survey includes a larger sample. We use the survey in 2015. The micro-level data are restricted use, and the BTI does not maintain a webpage with detailed information on the availability of the data. The BTI publishes an annual yearbook, Beijing Transportation Annual Reports, partly based on data from this survey. These annual reports are available to download at http://www.bjtrc.org.cn/List/index/cid/7/p/1.html. For more information, please visit BTIâs website. Phone, email, and other contact information is available at the contact page: http://www.bjtrc.org.cn/List/index/cid/16.html (all webpages in Chinese).

The 2015 intra-decennial census is a nationally representative 1% sample of population. It was conducted by the National Bureau of Statistics of China (NBS). A summary of the survey can be found at NBS's website: http://www.stats.gov.cn/tjsj/zxfb/201604/t20160420_1346151.html. Individual-level data of this survey is restricted access. Inquiries can be sent to NBS following the contact information listed on this page: http://www.stats.gov.cn/wzgl/201310/t20131022_445198.html (website in Chinese).

One version of the commuting time between any pair of home and work addresses is obtained from Baidu Maps (https://maps.baidu.com/). Baidu Maps makes some of their data available through commercial or academic collaboration. Applications can be submitted at https://jiaotong.baidu.com/contactus/(website in Chinese).

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