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A Structural Estimation of the Disutility of Commuting*

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Abstract

This study evaluates the disutility of long-distance commuting by structurally estimating a random utility model of commuting choice. Using estimated structural parameters for commuting preferences and considering the factors that produce heterogeneity across workers, the study quantifies the extent to which workers incur disutility from commuting under a counterfactual scenario in which they commute the same distance before and after marriage. Using inter-municipal commuting flow data in Japan, the counterfactual simulations uncover a significant gender gap in the disutility of commuting, particularly because having children after marriage greatly increases the disutility of commuting for female but not for male workers. Residential relocation plays a role in mitigating the disutility of commuting for female workers, implying that the additional disutility that arises after marriage can be offset through endogenous residential location choice.

JEL classification: J61, R23, R41
Keywords: Commuting, Utility, Structural estimation, Gravity equation

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1 Introduction

Urban congestion continues to worsen as urbanization accelerates, creating considerable inconvenience and cost for daily commuters. However, we have little information about what types of workers feel more stress from commuting and how much stress their commuting causes, owing to the difficulty in analyzing such physiological stress. To address these questions, this study aims to numerically evaluate the disutility of commuting, which could contribute greatly to the development of labor market and urban transportation policies.

The study uses a structural estimation to quantify the disutility of commuting. Although a basic microeconomic model assumes a utility function for individuals, their utility is not directly observable in reality. One could use subjective well-being as a proxy for utility, as Stutzer and Frey (2008), Morikawa (2018), and Jacob et al. (2019) did. This approach is straightforward and gives an intuitive understanding, but it suffers from the weakness that the measurement of well-being is based on subjective valuations, which makes it difficult to make a consistent comparison across individuals over time. In contrast, one of the most important reasons for using structural estimation is that this framework enables a model-based evaluation of utility, which can be combined with observed workers' commuting behavior. The use of structural estimation is essential when we need to measure the policy effects of a utility that is not directly observable.

This study contributes to the existing literature by focusing on heterogeneity in the disutility of commuting. Recent literature on urban economics has provided general equilibrium models that incorporate commuting decisions based on the principle of individual utility maximization, such as Ahlfeldt et al. (2015), Redding and Rossi-Hansberg (2017), Owens et al. (2017), Monte et al. (2018), Bryan and Morten (2018), and Heblich et al. (2018). One advantage of these studies is that they capture general equilibrium effects in a situation where commuting policies and costs can change. However, the assumption of a“ representative agent ”in a general equilibrium framework overlooks heterogeneity among workers, making it impossible to assess how urban transportation policies may affect workers' utility differently. Although this study relies on a partial equilibrium framework, its empirical results take into account rich information on workers' heterogeneity, such as age, gender, education, marital status, and residential relocation experience.[1]

[1]Tani (2002a,b) provides descriptive aspects of commuters with respect to gender, age, marital status, and family structure in the Greater Tokyo area. The present study takes these heterogeneities into account in developing its

Using data on all inter-municipal commuting flows and their relationship with various characteristics of workers in Japan, this study finds that having children is the biggest event that expands the gender gap in the disutility of commuting. Counterfactual simulations provide important numerical results. Under a scenario in which workers commute the same distance before and after marriage, whereas the utility level does not change significantly for male workers, it decreases drastically for female workers, and having children is the largest single contributor to the additional disutility. For example, the amount of monetary compensation needed to counteract the additional disutility of an 80-km round-trip commute for female workers with children age 6 to 15 is about 1.4 to 4.2 times as large as the wages they received before marrying. Obviously, this disutility is not compensated in the current Japanese labor market, and thus female workers need to shorten their commutes by changing jobs or workplaces if they wish to maintain the same utility level after marrying and having children. The present study's findings parallel those of Gimenez-Nadal and Molina (2016), who found that childcare time affects women's commuting behavior only and not that of their husbands. This study further finds that residential relocation plays a role in mitigating the disutility of commuting, implying that additional disutility after marriage can be offset by endogenous residential location choice. There is no difference in disutility between male and female workers who decide to relocate following marriage.

The study's findings indicate that workers accept the disutility of long-distance commuting if it can be offset by earning higher wages. This commuting choice leads to a positive correlation between nominal wages and commuting distance, as discussed previously by Timothy and Wheaton (2001), Fu and Ross (2013), Mulalic et al. (2014), Gutiérrez-i-Puigarnau et al. (2016), Dauth and Haller (2017), and Morikawa (2018). Whereas previous studies have directly considered the relationship between wages and commuting, this study suggests a structural estimation approach based on the decision-making process that underlies commuting behavior. In this way, the study advances the empirical literature on commuting.

The remainder of the paper is organized as follows. Section 2 describes available data on commuting in Japan. Section 3 explains a micro-foundation of commuting decisions, based on a random utility model and a structural estimation approach. Section 4 offers counterfactual simulations to quantify the disutility of commuting, and section 5 presents concluding remarks.

economic framework to measure the disutility of commuting.

2 Data

2.1 Municipality-Level Panel Data and Inter-Municipal Commuting

This study constructs a municipality-level panel dataset on inter-municipal commuting flows between 1980 and 2015 in Japan. One empirical issue to resolve in creating the dataset is that municipal borders have been changed by municipal mergers during this period. Even if the estimation of structural parameter is conducted every five years, the use of different geographic units makes it difficult to compare the estimation results throughout the entire period. This study uses the municipality converter for Japanese municipal panel data provided by Kondo (2019b).

Figure 1 shows the city hall locations of all municipalities in Japan. The number of Japanese municipalities as of October 1, 2015 was 1,741. Therefore, the total number of possible flows between municipalities, including intra-municipal commuting, is 3,031,081 ($1,741 \times 1,741$).

[Figure 1]

2.2 Commuting to Tokyo's 23 Wards from Suburban Areas

The baseline analysis is based on all 3,031,081 inter-municipal flows. To investigate heterogeneity in regional labor markets, this study also considers commuting flows in the Greater Tokyo area. For this analysis, the destination is stipulated as the 23 wards of Tokyo, and commuting flows within the 23 wards are excluded

Figure 2 shows the breakdown of municipalities of origin for these commutes, which are located in Ibaraki, Tochigi, Gunma, Saitama, Chiba, Tokyo, Kanagawa, and Yamanashi prefectures. Commuting flows from these 320 municipalities to Tokyo's 23 wards (7,460 = 320 $\times$ 23) are used in this additional analysis.

[Figure 2]

2.3 Commuting Flow Data in Population Census

This study uses a commuting flows dataset originally constructed from microdata of the Population Census (Ministry of Internal Affairs and Communications). The Population Census is conducted each five years. This study uses the censuses for the years 1980 to 2015. In years ending in the digit 0, an extended survey takes place; a simpler survey occurs in years that end with a 5.

The most important advantage of the Population Census is that it covers all residents of Japan. This is a crucial feature for an empirical analysis of interregional commuting flows, since instances of zero flows (i.e., municipality pairs between which people do not commute at all) also provide information on individuals' commuting decisions. The microdata contained in the Population Census allow us to consider aspects of heterogeneity among workers, such as age, gender, marital status, education, and residential relocation experience. Table 1 presents the classification of worker characteristics used in this study.

[Table 1]

The questionnaire of the Population Census asks respondents to indicate the municipality in which they work, and thus the commuting flow is defined as between this municipality and the one where that person usually lives. Commuting flows are aggregated at the municipal level to estimate a gravity equation.

The commuting distance is then calculated as the straight distance between the city hall locations of the two municipalities.[2] Based on Head and Mayer (2010), the intra-municipal distance is calculated as 2/3 times a radius of surface area, or $D_{ii} = 2/3\sqrt{\text{Area}_i/3.14}$, where Area_i is the area (km^2) of municipality i.

Table 2 presents descriptive statistics on commuting flows and distances for the full sample. Tables 3 and 4 present the descriptive statistics for males only and females only, respectively. Figure 3 shows a scatterplot of inter-municipal commuting flows and distances.

[Tables 2–4 and Figure 3]

3 Estimation Approach to Structural Parameter for Commuting

3.1 Micro-foundation of Commuting Decision

Recent studies in the urban economics literature have developed general equilibrium models of commuting choices based on a random utility model (e.g., Ahlfeldt et al., 2015; Redding and

[2]The city hall locations are obtained from the GIS software MANDARA. Some city hall locations are based on the former locations before the municipal mergers. The straight distance is calculated as the great-circle distance based on the Vincenty's formula using Stata's `geodist` command developed by Picard (2012).

Rossi-Hansberg, 2017; Heblich et al., 2018; Monte et al., 2018). This study constructs a simple random utility model concerning commuting decisions.

The model assumes that each worker decides on location i for living and location j for working as a pair, given the nominal wages and cost of living in each location, and then commutes between location i to location j. Workers choose optimal locations to maximize their utility. The total utility of each worker, U_{ij}, is defined as follows:

$$U_{ij} = V_{ij} b_{ij}, \quad \forall\, i, j, \tag{1}$$

where V_{ij} is the deterministic utility and $b_{ij} > 1$ is a stochastic factor of amenities related with locations i and j. This type of formulation is called a random utility model because a stochastic factor affects decision making.[3]

It is assumed that the deterministic utility V_{ij} is defined as the real wage discounted by commuting costs as follows:

$$V_{ij} = \frac{w_j}{P_i} \frac{1}{D_{ij}^{\delta}}, \tag{2}$$

where the real wage $\omega_{ij} = w_j / P_i$ is defined as the ratio between the nominal wages in location j and the cost of living in location i, and commuting costs $1/D_{ij}^{\delta}$ are expressed as a monotonic function with respect to commuting distance D_{ij} and with a distance-decay parameter δ. This specification means that, holding other things constant, a longer commuting distance leads to lower utility (i.e., disutility).[4].

The parameter δ determines the commuting preference structure for each worker. If the structural parameter δ takes the same value across workers, the same commuting distance leads to equal disutility for all of them. In this situation, commuting distance explains different utility levels across workers. On the other hand, if the structural parameter δ takes different values across workers, even the same distance of commuting will result in different levels of utility for different workers. A first goal of this study is to demonstrate preference heterogeneity

[3]The decision on whether an individual will work or not is omitted. In prior empirical literature, Gutiérrez-i-Puigarnau and van Ommeren (2010) investigated the impact of commuting distance on labor supply, and Black et al. (2014) discussed that how differences in commuting times across U.S. metropolitan areas affected labor supply of married female workers. Using German household panel data, Carta and Philippis (2018) studied how husbands' commuting time affected the labor supply of wives.

[4]It is important to consider commuting time as well as commuting distance. Berliant and Tabuchi (2018) considered the non-linearity of commuting costs arising from both factors in a theoretical model. Tabuchi (2018) developed a theoretical model of commuting, in which the non-linearity arising from commuting time and commuting distance plays a key role in explaining residential patterns and income sorting.

regarding the structural parameter δ in the empirical analysis.

The heterogeneity of preferences concerning parameter δ can be discussed from two perspectives. The first aspect is related to the direct costs of commuting, which are assumed to be common across workers in the baseline analysis. However, workers who travels by train, by bus, and by car may have different direct costs of traveling the same distance. Additional analyses focusing on the commuting method are provided in the Online Appendix. The second aspect is related to the indirect and unobserved costs of commuting, which depend on workers' characteristics. For example, commuting the same distance can have different impacts on utility, which are reflected as a heterogeneity in structural parameter δ.

This study aims to estimate the structural parameter δ to measure the disutility of commuting by means of counterfactual simulations. An empirical problem in estimating this structural parameter governing preferences is that utility is not observable, which violates the condition for a reduced-form regression that the dependent and explanatory variables must be observable. On the other hand, structural estimation relies on the condition that behavior is observed as a result of an underlying optimization procedure. In other words, the structural parameter δ is estimated by observed data on commuting behaviors under a specific model of utility maximization.

Recent studies based on random utility models, such as Ahlfeldt et al. (2015), Redding and Rossi-Hansberg (2017), Heblich et al. (2018), and Monte et al. (2018), show that the preference structural parameter δ can be estimated by a gravity equation on commuting.[5]

It is assumed that a stochastic factor of amenities can be drawn from an independent Frécht distribution. distribution. The cumulative distribution function of the Frécht distribution, $F_{ij}(b)$, is expressed as follows:

$$F_{ij}(b) = \exp\left(-B_{ij} b^{-\alpha}\right), \quad B_{ij} > 0, \quad \alpha > 1, \tag{3}$$

where B_{ij} is a scale parameter reflecting average amenities from living in location i and working in location j as a pair, and α is a shape parameter reflecting the dispersion of amenities-related factors.[6]

[5] Ahlfeldt and Wendland (2016) proposed another approach because commuting flows are not always available. Their estimation results show that non-linear regression on employment potential leads to values close to those obtained from a gravity model of commuting.

[6] Previous studies in the new economic geography literature also developed a random utility model of migration, in which the Gumbel distribution is assumed for stochastic amenities (e.g., Tabuchi and Thisse, 2002; Murata, 2003,

A worker is assumed to select the choice that maximizes utility among all possible choices. The assumption of a Fréсht distribution yields the probability of commuting from location i to location j as follows:

$$\pi_{ij} = \frac{B_{ij} w_j^{\alpha} P_i^{-\alpha} D_{ij}^{-\alpha\delta}}{\sum_{r=1}^{N} \sum_{s=1}^{N} B_{rs} w_s^{\alpha} P_r^{-\alpha} D_{rs}^{-\alpha\delta}}. \tag{4}$$

The probability of commuting to j conditional on living in location i, or $\pi_{ij|i}$, is derived as follows:

$$\pi_{ij|i} = \frac{\pi_{ij}}{\pi_i^{Residence}} = \frac{B_{ij} w_j^{\alpha} D_{ij}^{-\alpha\delta}}{\sum_{j=1}^{N} B_{ij} w_j^{\alpha} D_{ij}^{-\alpha\delta}}, \tag{5}$$

where $\pi_i^{Residence}$ is the probability of living in location i, derived by summing across workplaces:

$$\pi_i^{Residence} = \sum_{j=1}^{N} \frac{B_{ij} w_j^{\alpha} P_i^{-\alpha} D_{ij}^{-\alpha\delta}}{\sum_{r=1}^{N} \sum_{s=1}^{N} B_{rs} w_s^{\alpha} P_r^{-\alpha} D_{rs}^{-\alpha\delta}}. \tag{6}$$

Note that the probability of commuting to j conditional on living in location i take into account cost of living P_i. Given the location of one's residence, commuting choice i depends on nominal wages and commuting distance. A worker chooses a location with the highest result when nominal wages are discounted by commuting costs.

Under this structure, expected commuting flows from location i to location j, C_{ij}, are obtained below:

$$C_{ij} = \pi_{ij|i} \times L_i \tag{7}$$

where L_i represents the number of workers residing in location i.

Finally, substituting equation (5) into the above equation and taking the logarithm of both sides yields a gravity equation of commuting:

$$\log C_{ij} = \log B_{ij} - \alpha\delta \log D_{ij} + \log L_i - \log\left(\sum_{j=1}^{N} B_{ij} w_j^{\alpha} D_{ij}^{-\alpha\delta}\right) + \alpha \log w_j, \quad \forall\, i, j. \tag{8}$$

This study estimates structural parameter δ from the coefficient of the commuting distance of the gravity equation of commuting (8). Note that the shape parameter of Frécht distribution α and the structural parameter δ are not separately identified. In the literature, a shape parameter of a Frécht distribution has a limited range. For this reason, this study estimates δ as an interval,

2007; Crozet, 2004; Kondo and Okubo, 2015). Focusing on profit maximization, Eaton and Kortum (2002) developed a trade model assuming a Fréchet distribution of stochastic productivity factors in production.

given a reasonable range of shape parameter α.[7]

3.2 Estimation of Structural Parameters

A gravity equation of commuting (8) can be expressed as follows:

$$\log C_{ij} = \log B_{ij} - \alpha\delta \log D_{ij} + \varphi_i + \psi_j, \quad \forall\, i, j, \tag{9}$$

where φ_i and ψ_j are origin and destination fixed effects as expressed below:

$$\varphi_i = \log L_i - \log\left(\textstyle\sum_{j=1}^{N} B_{ij} w_j^{\alpha} D_{ij}^{-\alpha\delta}\right) \quad \text{and} \quad \psi_j = \alpha \log w_j. \tag{10}$$

Note that this gravity equation of commuting (8) includes the so-called "multilateral resistance" term discussed by Anderson and van Wincoop (2003), which is a potential source of bias if not controlled for. To control for multilateral resistance terms, this study introduces origin and destination fixed effects.

Furthermore, the existing literature points out estimation issues concerning the log-linearized gravity equation (8). The first estimation issue is zero flow. Taking the logarithm implies dropping cases of zero flow. However, dropping zero flows would result in the omission of potential choices. The second estimation issue arises from skewed distribution when zero flows are included, which causes bias of the standard errors. For these reasons, this study relies on the Poisson regression approach proposed by Silva and Tenreyro (2006).[8]

$$\begin{aligned} &\Pr(C_{ij} = c_{ij}) = \frac{\exp\Big(-\lambda_{ij}(\boldsymbol{\theta})\Big)\Big(\lambda_{ij}(\boldsymbol{\theta})\Big)^{c_{ij}}}{c_{ij}!}, \quad c_{ij} = 0, 1, 2, \ldots, \\ &\lambda_{ij}(\boldsymbol{\theta}) \equiv \exp\Big(-\nu \log D_{ij} + \varphi_i + \psi_j\Big), \end{aligned} \tag{11}$$

where $\boldsymbol{\theta}$ is a parameter vector to be estimated, $\nu = \alpha\delta$, φ_i is an origin fixed effect, ψ_j is a destination fixed effect. Note that the distance elasticity ν is estimated as a whole, and α and δ cannot be identified separately. In counterfactual simulations, the structural parameter δ is

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[7]The same problem arises in gravity equations regarding trade. A gravity model derived from a Dixit-Stitglitz monopolistic model has a composite parameter based on elasticity of substitution and the distance-decay of trade cost. A gravity model derived from firm heterogeneity with a Pareto distribution has a composite parameter based on the shape parameter of the Pareto distribution and the distance-decay of trade cost (Melitz and Redding, 2014, p. 26)

[8]The number of municipalities in the dataset is 1,741 in the data, as noted above, and introducing origin and destination dummies into the regression makes it difficult to estimate heteroskedasticity-consistent standard errors.

derived as $\hat{\delta} = \hat{\nu}/\alpha$, given the shape parameter α of the Fréchet distribution.

3.3 Estimation Results Using All Inter-Municipal Commuting Flows

Figure 4 presents estimation results for parameter ν in gravity equation (11).[9] The estimated value in Panel (a) shows a gradual decrease from 3.217 in 1980 to 2.742 in 2015. Panel (b) shows a comparison between male and female workers. In 1980, the estimated parameters are 2.987 for males and 3.817 for females. The gap shrinks gradually over time, but female workers still show higher values of the parameter in 2015 (2.576 for males and 3.033 for females). Although the heterogeneity in commuting preferences is simplified in a standard general equilibrium framework, the critical nature of the gender gap emerges clearly.

Figure 5 presents estimation results for parameter ν in the gravity equation (11) by worker characteristics (age, marriage status, education, and residential relocation). Figure 5, Panels (a)–(d) show large heterogeneity in commuting preferences for all four age groups (15–29, 30–44, 45–59, 60 and above). Older workers exhibit higher distance elasticity, meaning that the disutility of commuting is larger for elderly workers than for younger workers traveling the same distance. Interestingly, there is no significant gender gap for the 15–29 age group, whereas there is a significant gender-based difference for workers age 30 and above. This finding is consistent with Sakanishi (2007), who used Person Trip Survey data for the Kyoto-Osaka-Kobe area.

Figure 5, Panels (e)–(h) show large heterogeneity in commuting preferences by marital status. Importantly, the distance elasticity is unchanged for male workers before and after marriage, whereas it changes drastically for female workers. Just as with young workers, there is no gender gap for single workers. However, marrying affects only female workers' preferences with regard to commuting, not those of males.

Panels (i)–(l) of Figure 5 present estimation results of distance elasticity by education level. Relative to non-university graduates, university graduates exhibit lower distance elasticity. In addition, there is no gender gap for single workers who are university graduates and non-university graduates. As for married workers, the gender gap is smaller for married workers who are university graduates.

Panels (m)–(p) of Figure 5 present estimation results of distance elasticity by residential relocation status. Interestingly, the analysis demonstrates that residential relocation has played

[9] Tables of estimation results are provided in the Online Appendix.

a key role in reducing the disutility of commuting in recent years. Panel (p) shows that there was no significant gender gap for married workers with residential relocation experience in 2010 or 2015. These findings suggest that the disutility of commuting is averted by residential mobility after marriage.

[Figures 4–5]

3.4 Estimation Results in Greater Tokyo Area

Figures 6–7 present estimation results for parameter ν in gravity equation (11) using data on commuting to Tokyo's 23 wards from suburban areas. Compared to previous results, in general, gender differences in distance elasticity do not shrink over time in this analysis. For example, the gender gap expands over time for workers age 45 to 59, as shown in Panel (c) of Figure 7 and for married workers age 49 and under and with children age 6 to 15, as indicated in Panel (h) of Figure 7.

Also, male workers generally show lower distance elasticities that those estimated by commuting data across all municipalities in Figure 4. The distance elasticity decreases over time, implying that male workers in Greater Tokyo area can commute longer distances without reducing their utility.

These estimation results lead us to expect a large heterogeneity across regional labor markets. One reason for this heterogeneity concerns the commuting method used. Workers who commute to Tokyo's 23 wards generally travel by train. Additional results by the commuting method are offered in the Online Appendix.

[Figures 6–7]

4 Counterfactual Evaluation for Disutility of Commuting

4.1 Setting for the Counterfactuals

The counterfactuals assume that a worker commutes the same distance before and after marriage, and in this setting we can measure the extent to which marriage incurs additional disutility from commuting. The deterministic utility $V_{ij,g}$ is expressed as follows:

$$V_{ij,g} = \frac{w_{j,g}}{P_{i,g}} \frac{1}{D_{ij,g}^{\delta_g}}, \tag{12}$$

where $g \in (single, married)$ distinguishes between two states, single and married. Note that structural parameter $\hat{\delta}_g$ is estimated from $\hat{\delta}_g = \hat{\nu}_g/\alpha$, given $\alpha \in (2, 8)$. In other words, the counterfactuals measure utility change induced by a change in marital status from single to married.

The utility change before and after marriage can be expressed as follows:

$$\begin{aligned} \log V_{ij,married} - \log V_{ij,single} = \log w_{j,married} - \log w_{j,single} \\ - (\log P_{i,married} - \log P_{i,single}) \\ - (\hat{\delta}_{married} \log D_{ij,married} - \hat{\delta}_{single} \log D_{ij,single}), \end{aligned} \tag{13}$$

where the utility change consists of changes in three factors. The first, second, and third lines on the right-hand side of the equation capture differences in nominal wages, cost of living, and commuting costs, respectively.

The assumption used in the counterfactuals that a worker continues to commute the same distance means that $D_{ij} = D_{ij,married} = D_{ij,single}$. In addition, it is assumed that the cost of living does not change: $\log P_{i,married} = \log P_{i,single}$. Imposing the condition to ensure the same level of utility before and after marriage means that $\log V_{ij,married} - \log V_{ij,single} = 0$. Under this condition, the compensation for disutility of commuting can be derived as follows:

$$\log w_{j,married} - \log w_{j,single} - (\hat{\delta}_{married} - \hat{\delta}_{single}) \log D_{ij} = 0. \tag{14}$$

Manipulating this equation yields the following condition:

$$\frac{w_{j,married}}{w_{j,single}} = D_{ij}^{\hat{\delta}_{married} - \hat{\delta}_{single}}. \tag{15}$$

This condition measures the utility change related to commuting. Again, the key assumption here is that a worker continues to commute the same distance before and after marrying. Under this assumption, the utility does not change if structural parameter δ remains the same. If marriage affects preferences for commuting, the structural parameter changes, leading to a utility change even if the commuting distance does not change. Change in the structural parameter before and after marriage is captured by $\hat{\delta}_{married} - \hat{\delta}_{single}$. If this term is positive, a worker incurs disutility from commuting.

4.2 Counterfactual Simulation Results

Figures 8 and 9 illustrate the counterfactual simulation results related to marriage, using the structural parameter as estimated by data on commuting across all municipalities and by data on commuting to Tokyo's 23 wards, respectively. The vertical axis indicates the disutility of commuting in terms of the monetary amount needed to compensate for it, which is measured relative to nominal wages before marriage based on equation (15). The baseline value is 1, which means that there is no additional disutility of commuting. The horizontal axis indicates the round-trip commuting distance (in km).

Figures 8 and 9 clearly show a gender gap in the disutility of commuting. Female workers face additional disutility related to commuting after marriage, but male workers do not. For example, Panel (f) shows that the additional disutility of commuting after marriage is extremely high for female workers with children age 6 to 15. The monetary compensation amount reaches about 1.4 to 4.2 times as large as the wages received before marriage in Figure 8 and is 1.8 to 9.7 times as large in Figure 9. Comparing the two ranges indicates that female workers with children age 6 to 15 who commute to Tokyo's 23 wards incur a larger disutility of commuting than those working in other regions.

Furthermore, married female workers without children do not exhibit such a high disutility of commuting. This result suggests that having children after marriage is the main factor that makes it difficult for female workers to commute long distances. This finding is consistent with the fact that most female workers tend to quit their jobs after having children, because the wages paid to them are insufficient to counteract their greater disutility. Presumably, some female workers who want to continue working anticipate this situation and decide not to have children.

An interesting finding is that higher education alleviates the disutility of commuting after marriage for female workers, as shown in Panels (h) and (j), suggesting that university graduates frequently earn sufficiently high wages to offset the disutility of commuting. On the other hand, it is difficult for high-school graduates to offset the disutility of long-distance commuting by earning higher wages.

Furthermore, residential relocation plays an important role in mitigating the disutility of commuting, especially for female workers. In Panels (l) and (n), disutility of commuting is not observed for female migrants before and after marriage, suggesting that residential mobility offsets the additional disutility of commuting. Female workers may move closer to their workplace, so that they can commute a shorter distance, or they move to a location where the cost of living is sufficiently low to offset the additional disutility of commuting. In these ways, residential relocation can help females to continue working without additional disutility due to commuting.

As discussed by Matsushima et al. (2013) and Kawabata and Abe (2018), commuting is determined by individuals' endogenous decision making on where they will live and work. Since individuals incur greater disutility related to commuting after marriage, changes in residential and/or work location that ensure at least the same level of utility should be observed. Clark et al. (2003) pointed out that residential mobility is easier than changing one's workplace. Therefore, residential mobility plays a leading role in compensating for the disutility of commuting by either shortening one's commuting distance or reducing one's cost of living.[10]

[Figure 8]

5 Concluding Remarks

This study has proposed a simple structural estimation framework based on utility maximization. The advantage of structural estimation is that it allows us to evaluate utilities that are not directly observable in the real world. Counterfactual simulations allow us to quantify changes in the disutility of commuting.

This study has evaluated the disutility of commuting in monetary terms by means of counterfactual simulations, and it has also considered how marriage and having children, as major life events that influence one's employment situation, expand the gender gap in the disutility of commuting. Under the counterfactual scenario in which workers commute the same distance before and after marriage, only female workers experience a larger disutility of commuting after marrying. In fact, the amount of monetary compensation needed to counteract the additional disutility of an 80 km round-trip commute for female workers with children age 6 to 15 after marriage is about 1.4 to 4.2 times as large as the wages these females were receiving before they married. In contrast, the required monetary compensation for female workers without children in the same situation is about 1.1 to 1.7 times their pre-marriage wages.

[10] Kondo (2019a) investigates residential migration across municipalities in Japan.

These data suggest that having children after marriage is the primary factor generating a larger disutility of commuting.

These findings strongly suggest the need for policy interventions in the labor market and urban transportation. The conventional structure of Japanese society, characterized by the general perception that women should be the primary caregivers for children, results in greater stress only for female workers who want to keep working after marrying and having children. Increasing flexibility in the workplace might reduce the disutility of commuting for female workers. As observed by Persson and Rossin-Slater (2019), promoting workplace flexibility for fathers may also be helpful.

Moreover, this study has important implications for policy evaluation. Although we implicitly know that there is a gender gap in labor markets, we do not know how large the gender gap is. Since individual utility is not directly observable, planning specific policy interventions to address the gender gap becomes difficult. An important contribution of this study is to estimate quantitatively the size of the gender gap in disutility of commuting. The use of structural estimation is thus invaluable when policymakers seek to evaluate the extent to which their policies affect utility.

References

Ahlfeldt, Gabriel M., Wendland, Nicolai, 2016. The spatial decay in commuting probabilities: Employment potential vs. commuting gravity. Economics Letters 143, 125–129.

Ahlfeldt, Gabriel M., Redding, Stephen J., Sturm, Daniel M., Wolf, Nikolaus, 2015. The economics of density: Evidence from the Berlin Wall. Econometrica 83 (6), 2127–2189.

Anderson, James E., van Wincoop, Eric, 2003. Gravity with gravitas: A solution to the border puzzle. American Economic Review 93 (1), 170–192.

Berliant, Marcus, Tabuchi, Takatoshi, 2018. Equilibrium commuting. Economic Theory 65 (3), 609–627.

Black, Dan A., Kolesnikova, Natalia, Taylor, Lowell J., 2014. Why do so few women work in New York (and so many in Minneapolis)? Labor supply of married women across US cities. Journal of Urban Economics 79, 59–71.

Bryan, Gharad, Morten, Melanie, 2018. The aggregate productivity effects of internal migration: Evidence from Indonesia. Journal of Political Economy forthcoming.

Carta, Francesca, Philippis, Marta De, 2018. You've come a long way, baby. Husbands' commuting time and family labour supply. Regional Science and Urban Economics 69, 25–37.

Clark, William A.V., Huang, Youqin, Withers, Suzanne, 2003. Does commuting distance matter?: Commuting tolerance and residential change. Regional Science and Urban Economics 33 (2), 199–221.

Crozet, Matthieu, 2004. Do migrants follow market potentials? An estimation of a new economic geography model. Journal of Economic Geography 4 (4), 439–458.

Dauth, Wolfgang, Haller, Peter, 2017. Asymmetric wage responses to changes in commuting distances. Mimeo. (URL: https://drive.google.com/file/d/0B0XwUjKN7IMIVGlCVmEwWkpHS0k/view).

Eaton, Jonathan, Kortum, Samuel, 2002. Technology, geography, and trade. Econometrica 70 (5), 1741–1779.

Fu, Shihe, Ross, Stephen L., 2013. Wage premia in employment clusters: How important is worker heterogeneity? Journal of Labor Economics 31 (2), 271–304.

Gimenez-Nadal, J. Ignacio, Molina, José Alberto, 2016. Commuting time and household responsibilities: Evidence using propensity score matching. Journal of Regional Science 56 (2), 332–359.

Gutiérrez-i-Puigarnau, Eva, van Ommeren, Jos N., 2010. Labour supply and commuting. Journal of Urban Economics 68 (1), 82–89.

Gutiérrez-i-Puigarnau, Eva, Mulalic, Ismir, van Ommeren, Jos N., 2016. Do rich households live farther away from their workplaces? Journal of Economic Geography 16 (1), 177–201.

Head, Keith, Mayer, Thierry, 2010. Illusory Border Effects: Distance Mismeasurement Inflates Estimates of Home Bias in Trade. in: van Bergeijk, Peter A. G., Brakman, Steven (Eds.) The Gravity Model in International Trade: Advances and Applications, Cambridge University Press, Cambridge, pp. 165–192 (chapter 6).

Heblich, Stephan, Redding, Stephen J., Sturm, Daniel M., 2018. The making of the modern metropolis: Evidence from London. NBER Working Paper No. 25047.

Jacob, Nikita, Munford, Luke, Rice, Nigel, Roberts, Jennifer, 2019. The disutility of commuting? The effect of gender and local labor markets. Regional Science and Urban Economics 77, 264–275.

Kawabata, Mizuki, Abe, Yukiko, 2018. Intra-metropolitan spatial patterns of female labor force participation and commute times in Tokyo. Regional Science and Urban Economics 68, 291–

303.

Kondo, Keisuke, 2019a. Monopolar concentration in Tokyo and promotion of urban-to-rural migration. RIETI Policy Discussion Paper 19-P-006 (in Japanese).

Kondo, Keisuke, 2019b. Municipality-level panel data and municipal mergers in Japan. RIETI Technical Paper No. 19-T-001 (in Japanese).

Kondo, Keisuke, Okubo, Toshihiro, 2015. Interregional labour migration and real wage disparities: Evidence from Japan. Papers in Regional Science 94 (1), 67–87.

Melitz, Marc J., Redding, Stephen J, 2014. Heterogeneous Firms and Trade. in: Gopinath, Gita, Helpman, Elhanan, Rogoff, Kenneth (Eds.) Handbook of International Economics, vol. 4, Elsevier, Amsterdam, pp. 1–54 (chapter 1).

Monte, Ferdinando, Redding, Stephen J., Rossi-Hansberg, Esteban, 2018. Commuting, migration, and local employment elasticities. American Economic Review. forthcoming.

Morikawa, Masayuki, 2018. Long commuting time and the benefits of telecommuting. RIETI Discussion Paper No. 18-E-025.

Mulalic, Ismir, Ommeren, Jos N. Van, Pilegaard, Ninette, 2014. Wages and commuting: Quasi-natural experiments' evidence from firms that relocate. Economic Journal 124 (579), 1086–1105.

Murata, Yasusada, 2003. Product diversity, taste heterogeneity, and geographic distribution of economic activities: Market vs. non-market interactions. Journal of Urban Economics 53 (1), 126–144.

Murata, Yasusada, 2007. Taste heterogeneity and the scale of production: Fragmentation, unification, and segmentation. Journal of Urban Economics 62 (1), 135–160.

Owens, Raymond III, Rossi-Hansberg, Esteban, Sarte, Pierre-Daniel, 2017. Rethinking Detroit. NBER Working Paper No. 23146.

Persson, Petra, Rossin-Slater, Maya, 2019. When dad can stay home: FathersY workplace flexibility and maternal health. NBER Working Paper No. 25902.

Picard, Robert, 2012. GEODIST: Stata module to compute geodetic distances. Statistical Software Components S457147, Boston College Department of Economics.

Redding, Stephen J., Rossi-Hansberg, Esteban, 2017. Quantitative spatial economics. Annual Review of Economics 9, 21–58.

Silva, J. M. C. Santos, Tenreyro, Silvana, 2006. The log of gravity. Review of Economics and Statistics 88 (4), 641–658.

Stutzer, Alois, Frey, Bruno S., 2008. Stress that doesn't pay: The commuting paradox. Scandinavian Journal of Economics 110 (2), 339–366.

Tabuchi, Takatoshi, 2018. Where do the rich live in a big city? RIETI Discussion Paper No. 18-E-020.

Tabuchi, Takatoshi, Thisse, Jacques-François, 2002. Taste heterogeneity, labor mobility and economic geography. Journal of Development Economics 69 (1), 155–177.

Tani, Kenji, 2002a. Changes in the links between home and work after marriage in the Tokyo metropolitan suburbs. Geographical Review of Japan 75 (11), 623–643. (in Japanese).

Tani, Kenji, 2002b. A cohort analysis of changes in commuting patterns in the Tokyo metropolitan area, 1990s. Saitama University Department of Geography Occasional Paper 22, 1–20. (in Japanese).

Timothy, Darren, Wheaton, William C., 2001. Intra-urban wage variation, employment location, and commuting times. Journal of Urban Economics 50 (2), 338–366.

Matsushima, Kakuya, Kobayashi, Kiyoshi, Fukui, Hiroshi, 2013. A trip mode choice model with endogeneity in explanatory variables. Journal of Japan Society of Civil Engineers, Ser. D3 (Infrastructure Planning and Management) 69 (5), I_511–I_521. (in Japanese).

Sakanishi, Akiko, 2007. Gender differences in travel-to-work area and commuting behavior. Journal of Applied Regional Science 12, 95–108. (in Japanese).

Appendix A Gravity Equation with Fixed Effects

This appendix explains how the use of origin and destination fixed effects offers a more flexible model specification, in the sense that a gravity model with origin and destination fixed effects does not depend on a specific model.

As explained in section 3 of the main text, the probability of commuting from i conditional on working in location j, $\pi_{ij|j}$, is given as follows

$$\pi_{ij|j} = \frac{\pi_{ij}}{\pi_j^{Workplace}} = \frac{B_{ij} P_i^{-\alpha} D_{ij}^{-\alpha\delta}}{\sum_{i=1}^{N} B_{ij} P_i^{-\alpha} D_{ij}^{-\alpha\delta}}, \tag{16}$$

where $\pi_j^{Workplace}$ is a probability of working in location j. This probability is derived by summing across residential locations:

$$\pi_j^{Workplace} = \sum_{i=1}^{N} \frac{B_{ij} w_j^{\alpha} P_i^{-\alpha} D_{ij}^{-\alpha\delta}}{\sum_{r=1}^{N} \sum_{s=1}^{N} B_{rs} w_s^{\alpha} P_r^{-\alpha} D_{rs}^{-\alpha\delta}}. \tag{17}$$

Note that the probability of commuting from i conditional on working in location j does not include wages w_j. Given that one is working in location j, commuting choice depends on cost of living and commuting distance. A worker can be expected to choose a location with the lowest combination of cost of living and commuting costs.

Under this structure, expected commuting flows from location i to location j, C_{ij}, are obtained below:

$$C_{ij} = \pi_{ij|j} \times L_j \tag{18}$$

where L_j represents the number of workers in location j.

Finally, substituting equation (16) into the above equation and taking the logarithm of both sides yields a gravity equation of commuting:

$$\log C_{ij} = \log B_{ij} - \alpha\delta \log D_{ij} - \alpha \log P_i + \log L_j - \log\left(\sum_{i=1}^{N} B_{ij} P_i^{-\alpha} D_{ij}^{-\alpha\delta}\right), \quad \forall\, i, j \tag{19}$$

A gravity equation of commuting (20) can be expressed as follows:

$$\log C_{ij} = \log B_{ij} - \alpha\delta \log D_{ij} + \eta_i + \mu_j, \quad \forall\, i, j \tag{20}$$

where η_i and μ_j are origin and destination fixed effects expressed below:

$$\eta_i = -\alpha \log P_i \quad \text{and} \quad \mu_j = \log L_j - \log\left(\sum_{i=1}^{N} B_{ij} P_i^{-\alpha} D_{ij}^{-\alpha\delta}\right) \tag{21}$$

Although gravity equation of commuting (20) has the same specification as equation (9), the original specifications differ between equations (8) and (19). To avoid a situation in which different specifications lead to different estimates of the distance elasticity $\nu = \alpha\delta$, this study estimates a gravity model with origin and destination fixed effects.

Table 1 Classification of Workers' Characteristics

Type	Content of Classification
All	- Full sample
Gender	- Male - Female
Age	- Male: (i) Age 15–29, (ii) Age 30–44, (iii) Age 45–59, (iv) Age 60 and above - Female: (i) Age 15–29, (ii) Age 30–44, (iii) Age 45–59, (iv) Age 60 and above
Marriage	- Male age 49 and under: (i) Single, (ii) Married without children (age 0–15), (iii) Married with children (age 0–5), (iv) Married with children (age 6–15) - Female age 49 and under: (i) Single, (ii) Married without children (age 0–15), (iii) Married with children (age 0–5), (iv) Married with children (age 6–15)
Education	- Male: (i) Single non-university graduates, (ii) Married non-university graduates, (iii) Single university graduates, (iv) Married university graduates - Female: (i) Single non-university graduates, (ii) Married non-university graduates, (iii) Single university graduates, (iv) Married university graduates
Residential relocation	- Male: (i) Single non-migrants, (ii) Married non-migrants, (iii) Single migrants, (iv) Married migrants - Female: (i) Single non-migrants, (ii) Married non-migrants, (iii) Single migrants, (iv) Married migrants

Note: Education information is not available in the 1985, 1995, 2005, and 2015 Population Censuses (Ministry of Internal Affairs and Communications); Residential relocation information is not available in the 1985, 1995, and 2005 Population Censuses (Ministry of Internal Affairs and Communications).

Table 2 Descriptive Statistics of the Full Sample

Variable		1980	1985	1990	1995	2000	2005	2010	2015
Commuting Flows	Average	492	424	414	392	371	338	340	271
(Unit: persons)	S.D.	7,935	7,448	7,491	7,307	6,985	6,526	6,223	5,500
	1st Percentile	1	1	1	1	1	1	1	1
	10th Percentile	1	1	1	1	1	1	1	1
	25th Percentile	1	1	1	1	1	1	1	1
	50th Percentile	3	2	2	2	2	2	2	2
	75th Percentile	18	13	13	13	13	12	14	9
	90th Percentile	169	130	134	128	127	113	136	84
	99th Percentile	8,406	6,535	6,281	5,829	5,491	4,968	5,168	4,017
	Observation	54,127,876	57,166,213	60,324,423	62,551,683	61,169,522	59,453,704	54,764,156	54,513,310
Commuting Distance	Average	87	160	161	163	162	177	162	208
(Unit: km)	S.D.	107	225	228	224	225	243	230	267
	1st Percentile	4	4	4	4	4	5	4	5
	10th Percentile	15	17	18	19	19	20	19	22
	25th Percentile	28	32	34	36	36	38	35	42
	50th Percentile	52	65	66	71	72	77	69	93
	75th Percentile	99	175	173	182	176	208	174	270
	90th Percentile	199	464	475	457	434	481	430	561
	99th Percentile	519	991	1,006	988	1,016	1,102	1,050	1,215
Inter-Municipal Flows	Nonzero Flows	109,997	134,803	145,681	159,508	164,935	176,100	161,209	201,170
	All Flows	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081
	Share of Nonzero Flows (%)	3.63	4.45	4.81	5.26	5.44	5.81	5.32	6.64

Note: Descriptive statistics are calculated without zero flows. Descriptive statistics of commuting flows and distance are aggregated at the municipal level as of October 1, 2015. Inter-municipal distance is based on the city hall location of each municipality.

Table 3 Descriptive Statistics of the Male Subsample

Variable		1980	1985	1990	1995	2000	2005	2010	2015
Commuting Flows	Average	312	265	257	243	228	205	203	159
(Unit: persons)	S.D	4,856	4,452	4,407	4,276	4,007	3,660	3,381	2,923
	1st Percentile	1	1	1	1	1	1	1	1
	10th Percentile	1	1	1	1	1	1	1	1
	25th Percentile	1	1	1	1	1	1	1	1
	50th Percentile	3	2	2	2	2	2	2	2
	75th Percentile	17	13	13	12	12	11	13	9
	90th Percentile	141	109	111	107	104	94	108	70
	99th Percentile	5,217	4,248	4,020	3,771	3,475	3,192	3,227	2,486
	Observation	33,522,932	34,875,148	36,415,636	37,618,023	36,243,903	34,631,632	31,238,719	30,647,920
Commuting Distance	Average	86	159	160	161	159	173	157	203
(Unit: km)	S.D.	107	225	227	222	221	236	224	261
	1st Percentile	4	4	4	4	4	5	4	5
	10th Percentile	15	17	18	19	19	20	18	21
	25th Percentile	28	32	33	35	35	37	34	41
	50th Percentile	51	64	65	69	70	75	67	91
	75th Percentile	97	174	169	179	172	202	168	264
	90th Percentile	197	464	472	454	428	471	420	551
	99th Percentile	517	990	999	982	999	1,056	1,021	1,175
Inter-Municipal Flows	Nonzero Flows	107,518	131,659	141,865	154,530	159,195	168,616	153,755	192,150
	All Flows	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081
	Share of Nonzero Flows (%)	3.55	4.34	4.68	5.10	5.25	5.56	5.07	6.34

Note: Descriptive statistics are calculated without zero flows. Descriptive statistics of commuting flows and distance are aggregated at the municipal level as of October 1, 2015. Inter-municipal distance is based on the city hall location of each municipality.

Table 4 Descriptive Statistics of the Female Subsample

Variable		1980	1985	1990	1995	2000	2005	2010	2015
Commuting Flows	Average	471	460	441	403	381	347	335	311
(Unit: persons)	S.D.	4,990	5,098	5,161	4,981	4,847	4,628	4,432	4,287
	1st Percentile	1	1	1	1	1	1	1	1
	10th Percentile	1	1	1	1	1	1	1	1
	25th Percentile	1	1	1	1	1	1	1	1
	50th Percentile	4	4	4	3	3	3	3	3
	75th Percentile	31	31	31	28	27	24	26	22
	90th Percentile	243	255	265	256	252	231	243	213
	99th Percentile	9,826	9,157	8,461	7,367	6,675	5,877	5,498	5,059
	Observation	20,604,944	22,291,065	23,908,787	24,933,660	24,925,619	24,822,072	23,525,437	23,865,390
Commuting Distance	Average	43	58	62	68	72	86	81	103
(Unit: km)	S.D.	62	113	120	128	139	171	159	198
	1st Percentile	2	2	3	3	3	3	3	3
	10th Percentile	8	9	9	10	10	11	11	12
	25th Percentile	15	16	17	19	20	21	21	22
	50th Percentile	27	29	31	34	35	37	36	39
	75th Percentile	47	51	54	60	62	70	66	80
	90th Percentile	81	100	107	126	133	175	159	257
	99th Percentile	348	623	633	708	816	902	880	967
Inter-Municipal Flows	Nonzero Flows	43,716	48,485	54,218	61,908	65,413	71,524	70,324	76,792
	All Flows	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081	3,031,081
	Share of Nonzero Flows (%)	1.44	1.60	1.79	2.04	2.16	2.36	2.32	2.53

Note: Descriptive statistics are calculated without zero flows. Descriptive statistics of commuting flows and distance are aggregated at the municipal level as of October 1, 2015. Inter-municipal distance is based on the city hall location of each municipality.

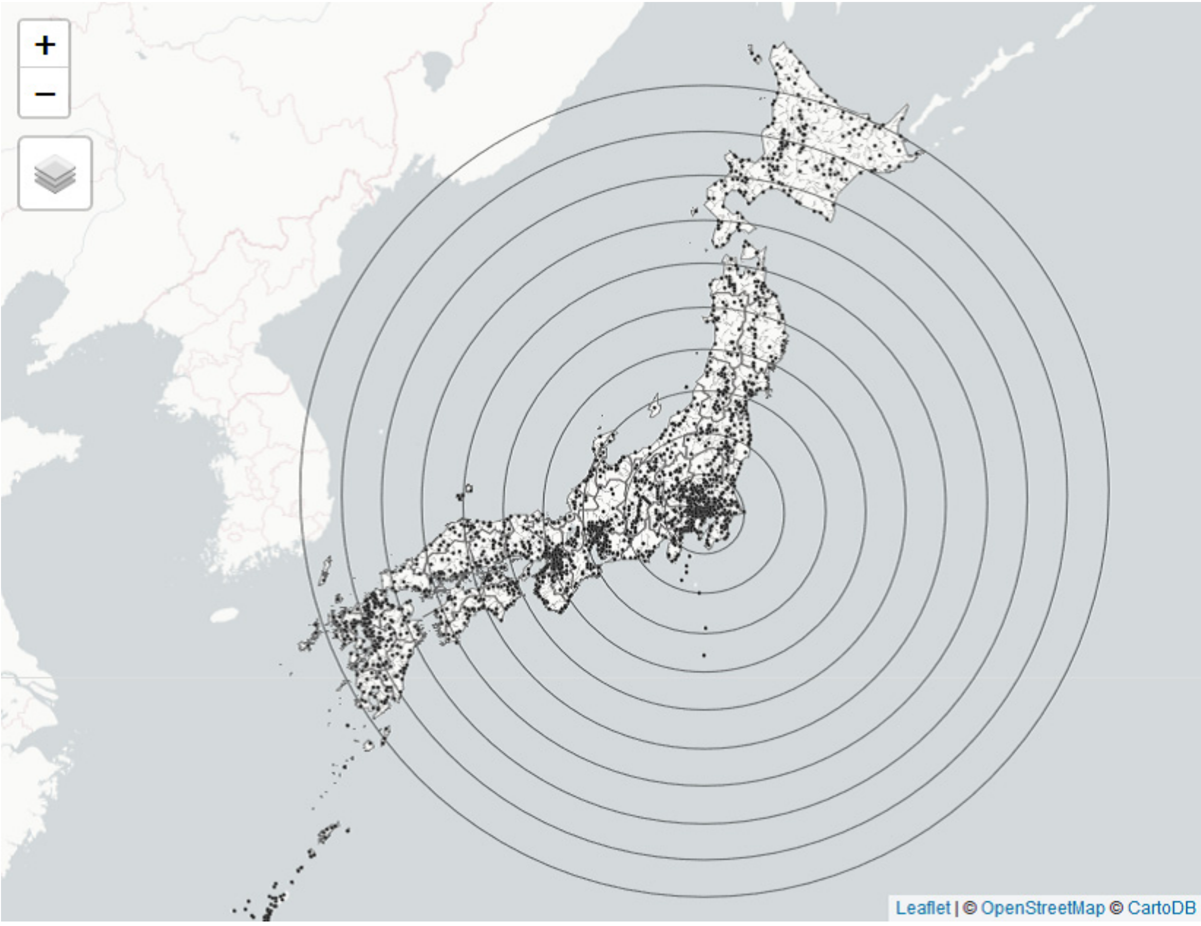


Figure 1: Commuting across All Municipalities in Japan

Note: The circles are depicted at 100 km intervals from the city hall location of Chiyoda-ku, Tokyo. The total number of possible flows between municipalities, including intra-municipal commuting, is 3,031,081 (= $1,741 \times 1,741$). Inter-municipal distance is calculated based on the city hall location of each municipality, which is shown as the black marker in the map. Some city hall locations are based on the former locations before the municipal mergers.
Source: Created by the author.

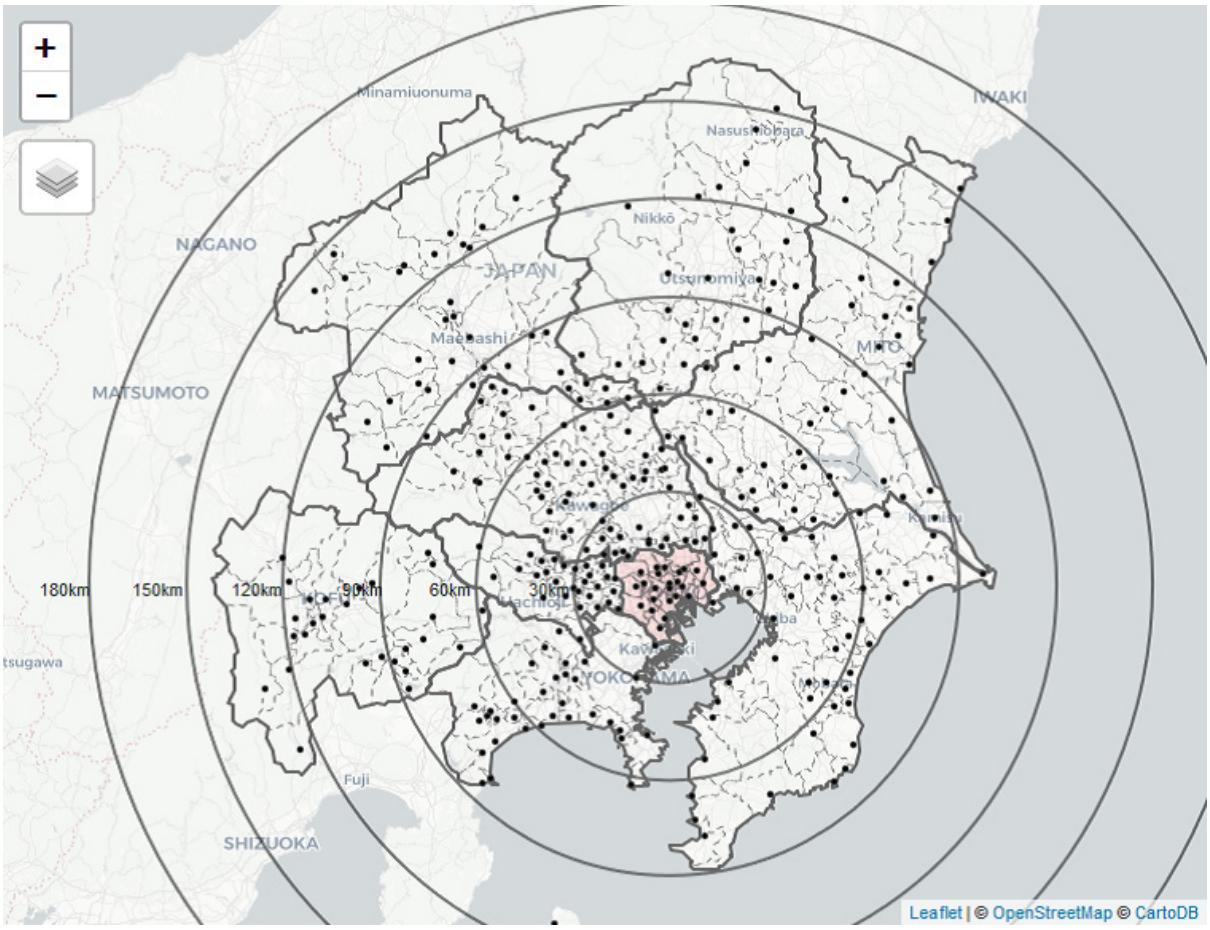
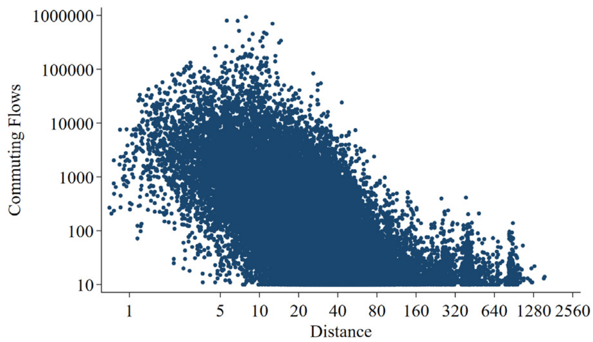
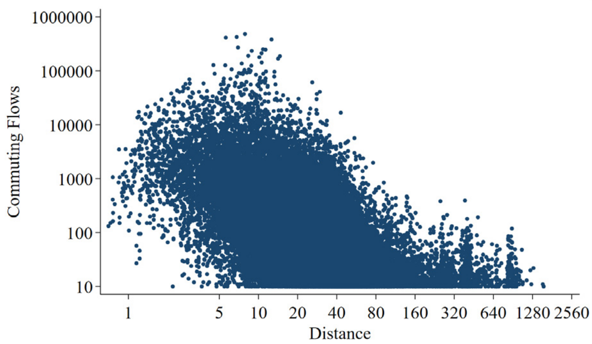


Figure 2: Commuting to Tokyo's 23 Special Wards from Suburban Areas

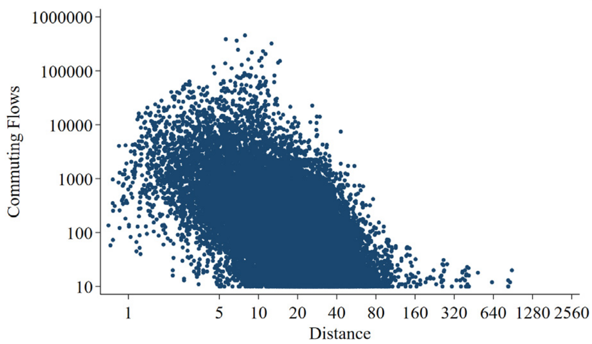
Note: The red-colored area in the map corresponds to the 23 special wards of Tokyo. The circles are depicted at 30 km intervals from the city hall location of Chiyoda-ku, Tokyo. The total number of commuting flows from the 320 municipalities in Ibaraki, Tochigi, Gunma, Saitama, Chiba, Tokyo, Kanagawa, and Yamanashi prefectures to Tokyo's 23 wards is 7,460 (= 320×23). Commuting flows within the special wards are excluded from the sample. Inter-municipal distance is calculated based on the city hall location of each municipality, which is shown as the black marker in the map. Some city hall locations are based on the former locations before the municipal mergers.
Source: Created by the author.



(a) Full Sample



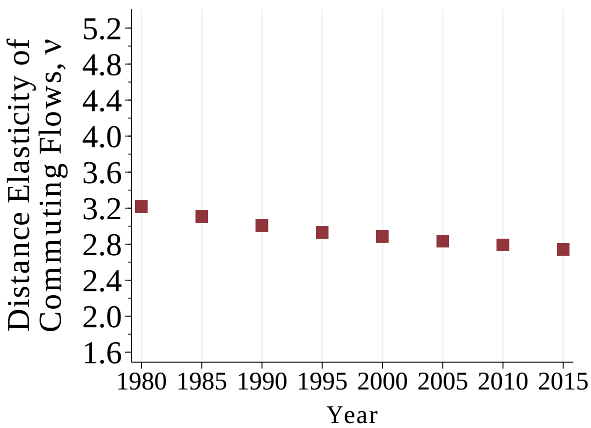
(b) Male Workers



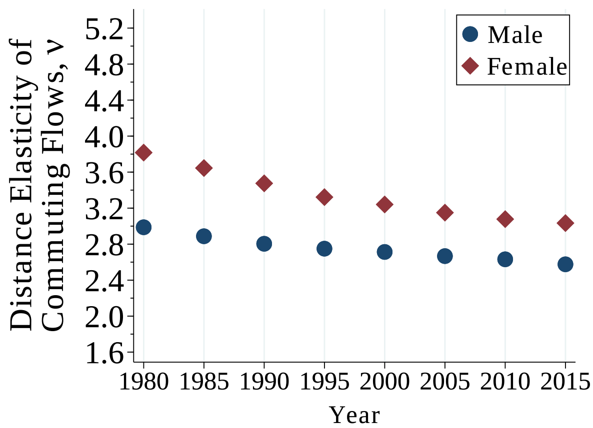
(c) Female Workers

Figure 3: Inter-Municipal Commuting Flows and Distance

Note: Created by the author using the 2010 Population Census (Ministry of Internal Affairs and Communications). Inter-municipal commuting flows below 10 persons are not reported here.



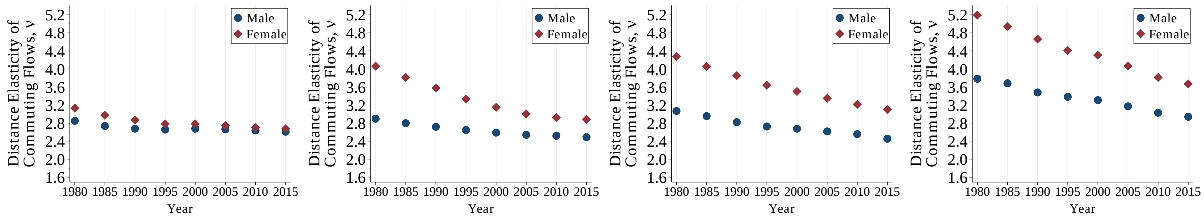
(a) Full Sample



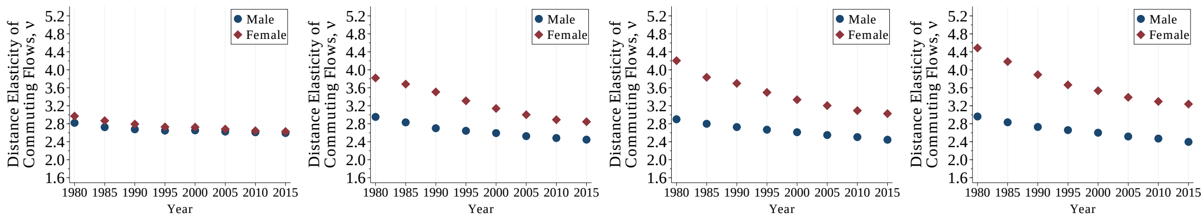
(b) Sample by Gender

Figure 4: Distance Elasticity of Commuting Flows Estimated from Data on Commuting across All Municipalities

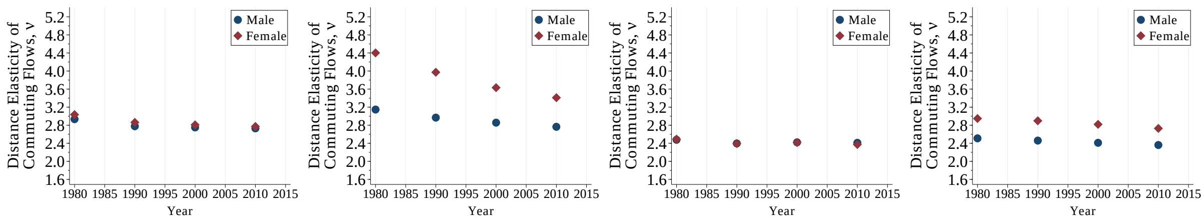
Note: Estimated by the Poisson regression with origin and destination fixed dummies.



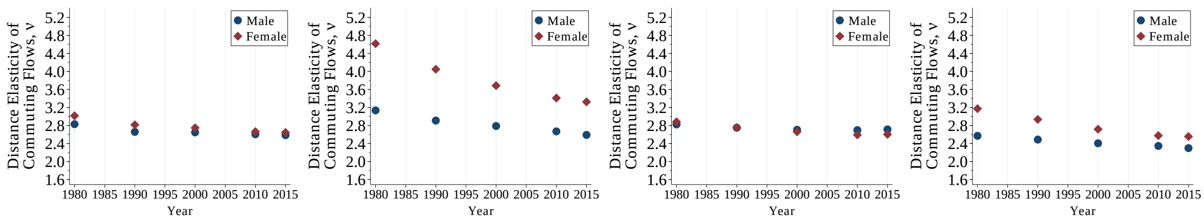
(a) Age 15–29 (b) Age 30–44 (c) Age 45–59 (d) Age 60 and above



(e) Single age ≤ 49 (f) Married age ≤ 49 without children (age 0–15) (g) Married age ≤ 49 with children (age 0–5) (h) Married age ≤ 49 with children (age 6–15)



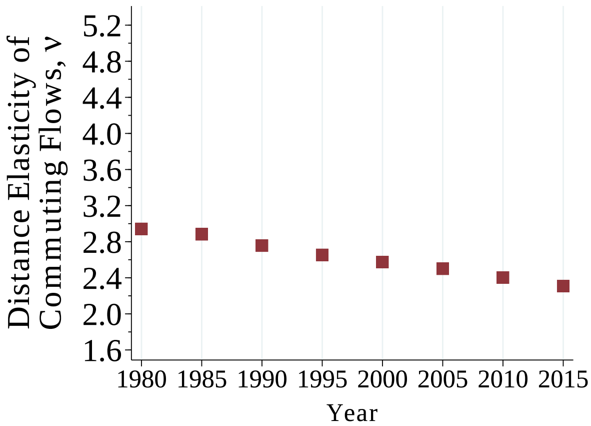
(i) Single non-university graduates (j) Married non-university graduates (k) Single university graduates (l) Married university graduates



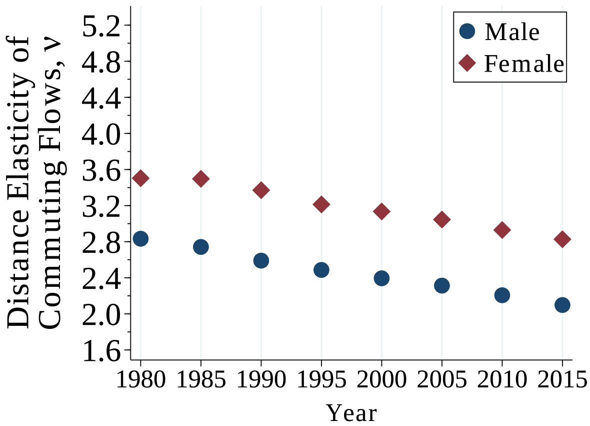
(m) Single non-migrants (n) Married non-migrants (o) Single migrants (p) Married migrants

Figure 5: Heterogeneity in Distance Elasticity of Commuting Flows Estimated from Data on Commuting across All Municipalities

Note: Estimated by the Poisson regression with origin and destination fixed dummies. Educational information is not available in the 1985, 1995, 2005, and 2015 Population Censuses (Ministry of Internal Affairs and Communications); migration information is not available in the 1985, 1995, and 2005 Population Censuses (Ministry of Internal Affairs and Communications).



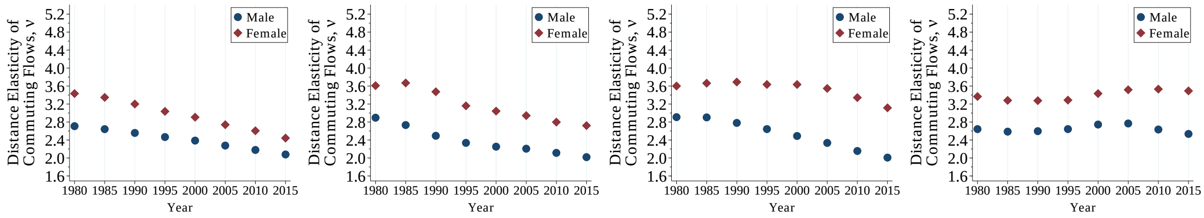
(a) Full Sample



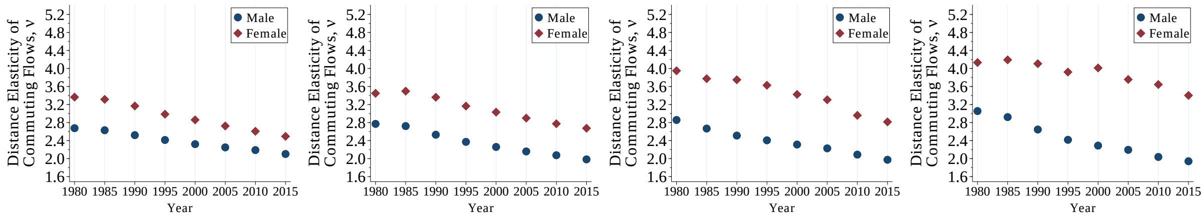
(b) Sample by Gender

Figure 6: Distance Elasticity of Commuting Flows Estimated by Commuting to Tokyo's 23 Wards

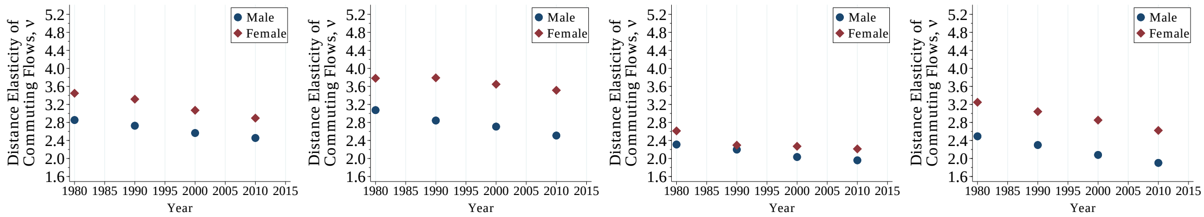
Note: Estimated by the Poisson regression with origin and destination fixed dummies.



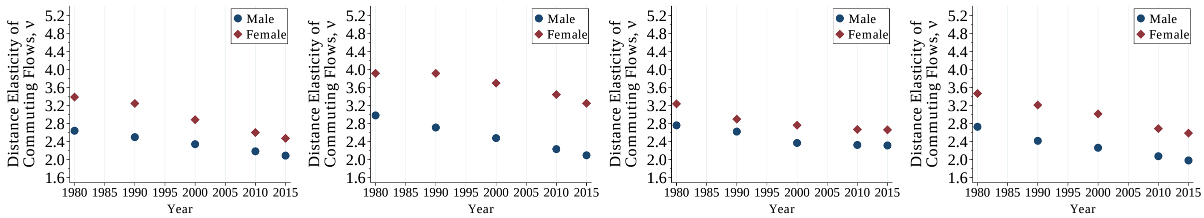
(a) Age 15–29 (b) Age 30–44 (c) Age 45–59 (d) Age 60 and above



(e) Single age ≤ 49 (f) Married age ≤ 49 without children (age 0–15) (g) Married age ≤ 49 with children (age 0–5) (h) Married age ≤ 49 with children (age 6–15)



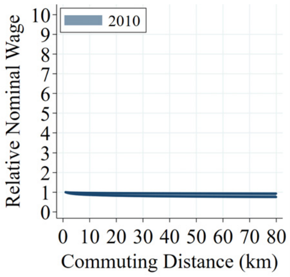
(i) Single non-university graduates (j) Married non-university graduates (k) Single university graduates (l) Married university graduates



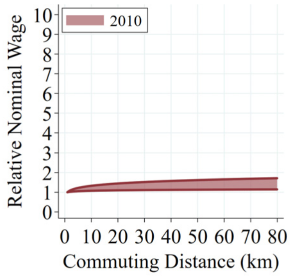
(m) Single non-migrants (n) Married non-migrants (o) Single migrants (p) Married migrants

Figure 7: Heterogeneity in Distance Elasticity of Commuting Flows Estimated from Data on Commuting to Tokyo's 23 Wards

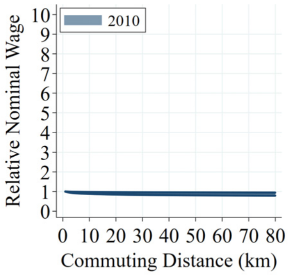
Note: Estimated by the Poisson regression with origin and destination fixed dummies. Education information is not available in the 1985, 1995, 2005, and 2015 Population Censuses (Ministry of Internal Affairs and Communications); migration information is not available in the 1985, 1995, and 2005 Population Censuses (Ministry of Internal Affairs and Communications).



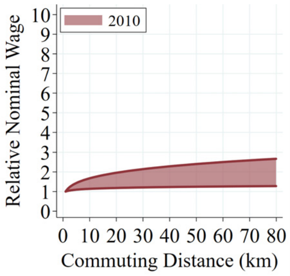
(a) Male,
without children (age 0–15)



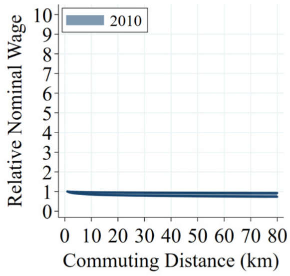
(b) Female,
without children (age 0–15)



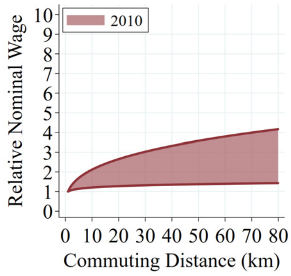
(c) Male, age ≤ 49
with children (age 0–5)



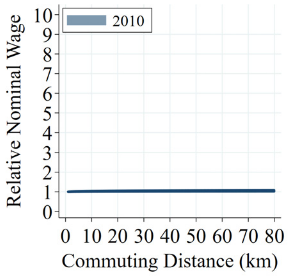
(d) Female, age ≤ 49
with children (age 0–5)



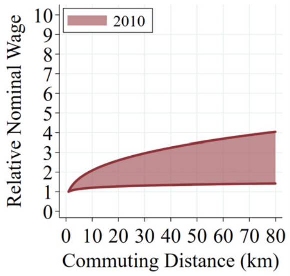
(e) Male, age ≤ 49
with children (age 6–15)



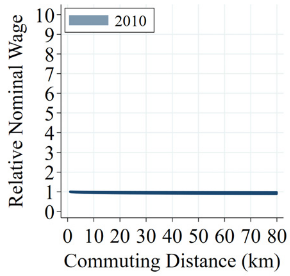
(f) Female, age ≤ 49
with children (age 6–15)



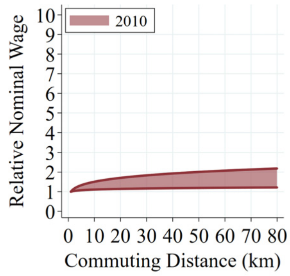
(g) Male,
non-university graduates



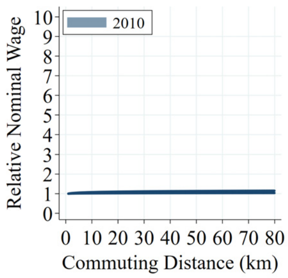
(h) Female,
non-university graduates



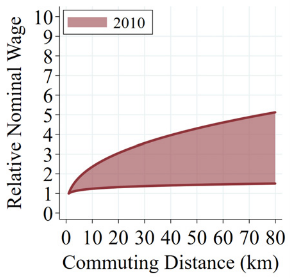
(i) Male,
university graduates



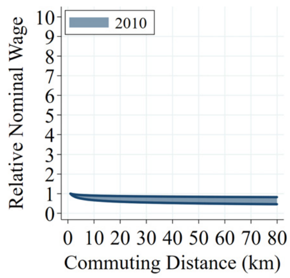
(j) Female,
university graduates



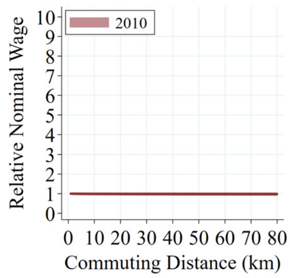
(k) Male,
non-migrants



(l) Female,
non-migrants



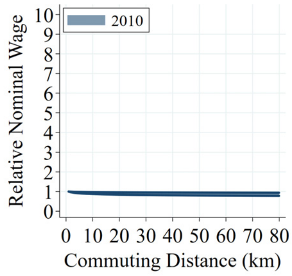
(m) Male,
migrants



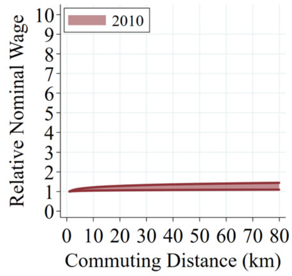
(n) Female,
migrants

Figure 8: Disutility of Commuting as Measured by Compensation before and after Marriage in 2010, Using Structural Parameters Estimated from Data on Commuting across All Municipalities

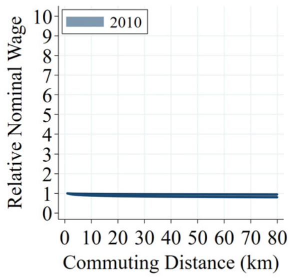
Note: The counterfactual assumes that a worker continues to commute the same distance before and after marriage, even if preferences on commuting change after marriage. The upper and lower bounds of disutility of commuting are based on the shape parameter $\alpha \in (2, 8)$ of the Fréchet distribution.



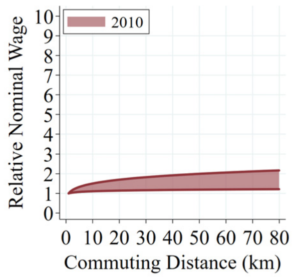
(a) Male,
without children (age 0–15)



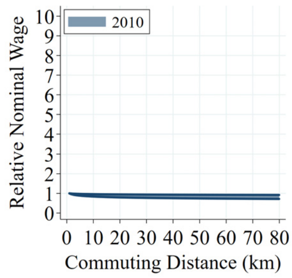
(b) Female,
without children (age 0–15)



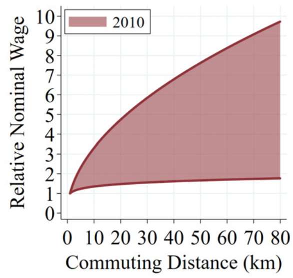
(c) Male, age ≤ 49
with children (age 0–5)



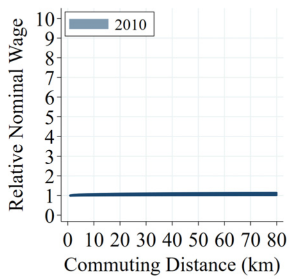
(d) Female, age ≤ 49
with children (age 0–5)



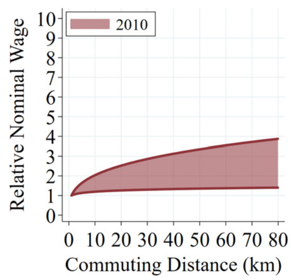
(e) Male, age ≤ 49
with children (age 6–15)



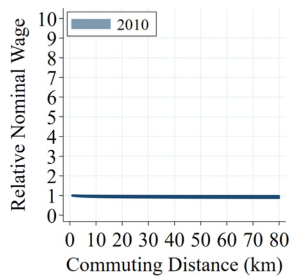
(f) Female, age ≤ 49
with children (age 6–15)



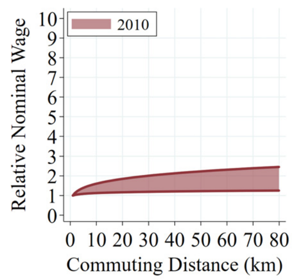
(g) Male,
non-university graduates



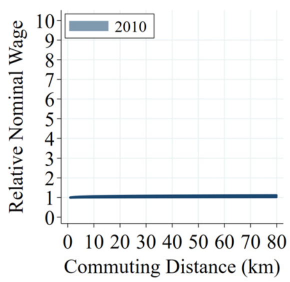
(h) Female,
non-university graduates



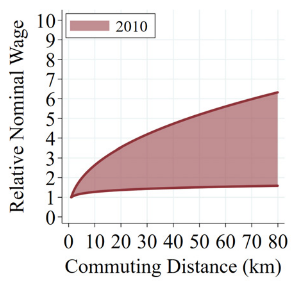
(i) Male,
university graduates



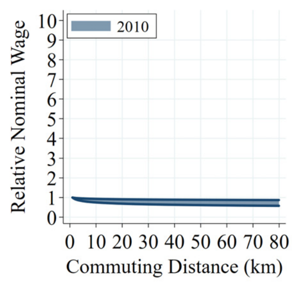
(j) Female,
university graduates



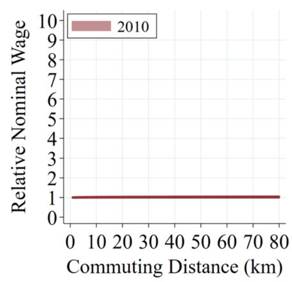
(k) Male,
non-migrants



(l) Female,
non-migrants



(m) Male,
migrants



(n) Female,
migrants

Figure 9: Disutility of Commuting as Measured by Compensation before and after Marriage in 2010, Using Structural Parameters Estimated from Data on Commuting to Tokyo's 23 Wards

Note: The counterfactual assumes that a worker continues to commute the same distance before and after marriage, even if preferences on commuting change after marriage. The upper and lower bounds of disutility of commuting are based on the shape parameter $\alpha \in (2, 8)$ of the Fréchet distribution.

Online Appendix

A Structural Estimation of Disutility of Commuting

This online appendix provides additional estimation results.

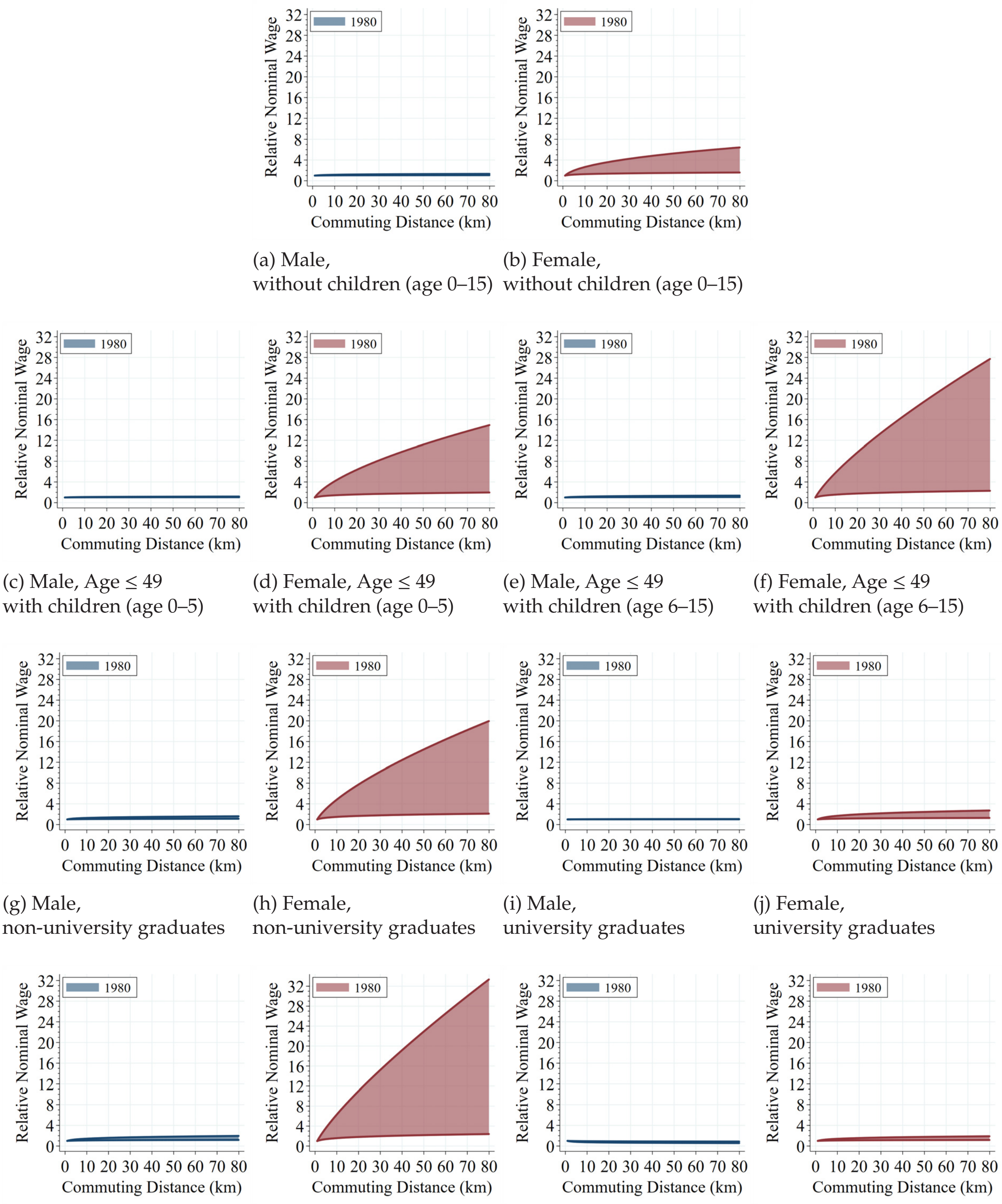
Contents

Online Appendix A.

Counterfactual Simulation Results using Structural Parameters in 1980

Figures OA A.1–OA A.2 present counterfactual simulation results using structural parameters in 1980, which correspond to Figures 7 and 8 in the paper.

[Figures OA A.1–OA A.2]



(a) Male, without children (age 0–15)

(b) Female, without children (age 0–15)

(c) Male, Age ≤ 49 with children (age 0–5)

(d) Female, Age ≤ 49 with children (age 0–5)

(e) Male, Age ≤ 49 with children (age 6–15)

(f) Female, Age ≤ 49 with children (age 6–15)

(g) Male, non-university graduates

(h) Female, non-university graduates

(i) Male, university graduates

(j) Female, university graduates

(k) Male, non-migrants

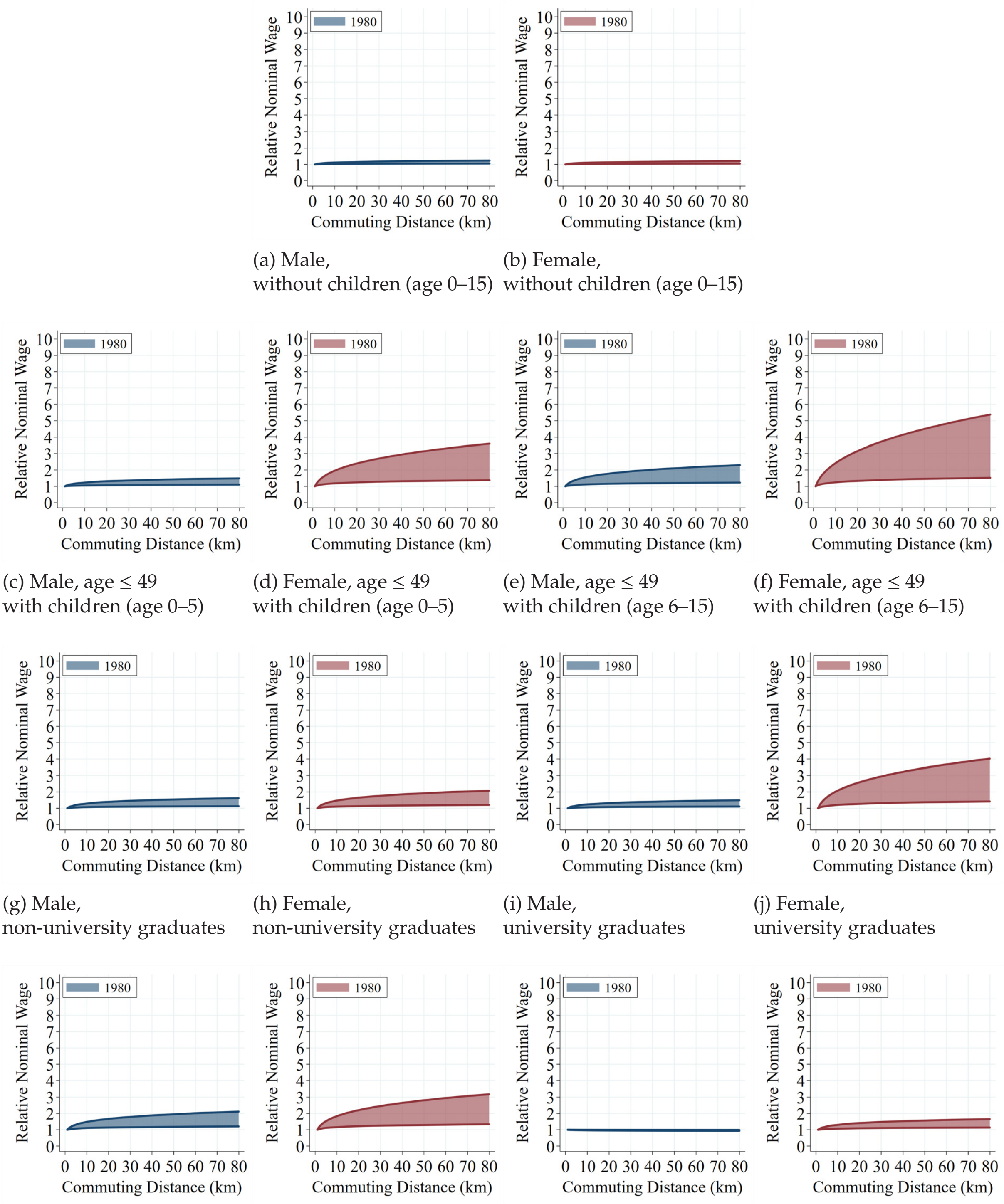
(l) Female, non-migrants

(m) Male, migrants

(n) Female, migrants

Figure OA A.1: Disutility of Commuting Measured by Compensation Wage Before and After Marriage in 1980 Using Structural Parameters Estimated from Data on Commuting across All Municipalities

Note: The counterfactual assumes that a worker continues to commute the same distance before and after marriage, even if preferences on commuting change after marriage. The upper and lower bounds of disutility of commuting are based on the shape parameter $\alpha \in (2, 8)$ of the Fréchet distribution.



(a) Male, without children (age 0–15)

(b) Female, without children (age 0–15)

(c) Male, age ≤ 49 with children (age 0–5)

(d) Female, age ≤ 49 with children (age 0–5)

(e) Male, age ≤ 49 with children (age 6–15)

(f) Female, age ≤ 49 with children (age 6–15)

(g) Male, non-university graduates

(h) Female, non-university graduates

(i) Male, university graduates

(j) Female, university graduates

(k) Male, non-migrants

(l) Female, non-migrants

(m) Male, migrants

(n) Female, migrants

Figure OA A.2: Disutility of Commuting Measured by Compensation Wage Before and After Marriage in 1980 Using Structural Parameters Estimated from Data on Commuting to Tokyo's 23 Wards from Suburban Areas

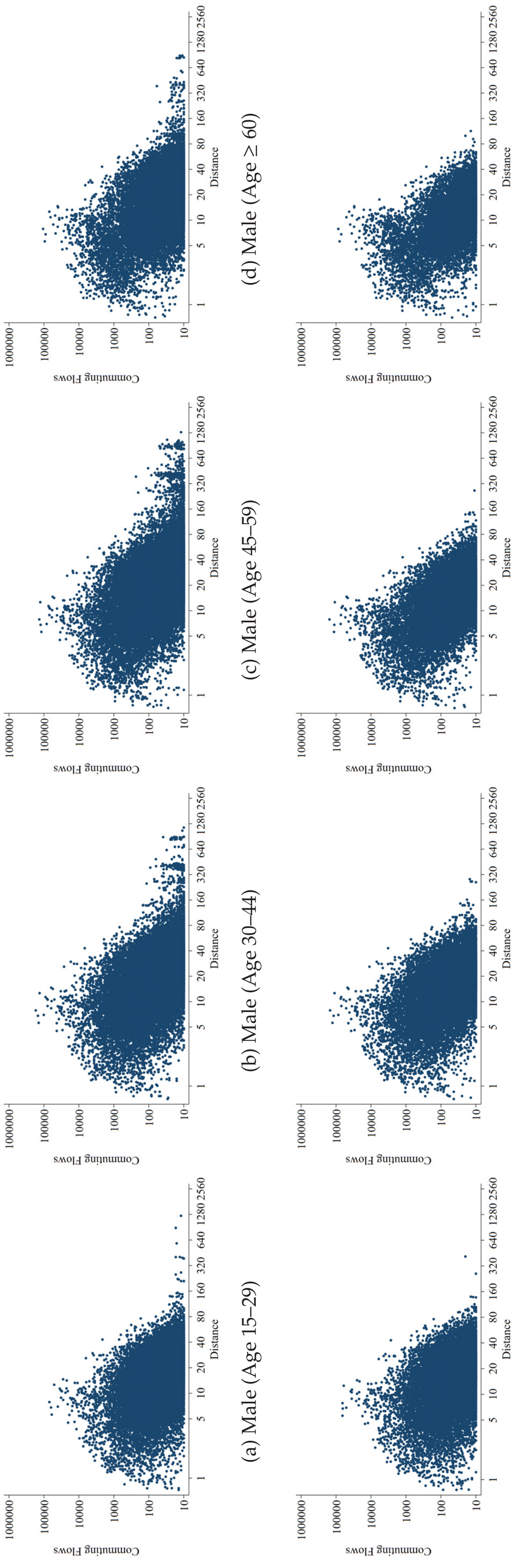
Note: The counterfactual assumes that a worker continues to commute the same distance before and after marriage, even if preferences on commuting change after marriage. The upper and lower bounds of disutility of commuting are based on the shape parameter $\alpha \in (2, 8)$ of the Fréchet distribution.

Online Appendix B.

Scatterplot of Commuting Flows and Distance

Figures OA B.1–OA B.5 show scatterplot between inter-municipal commuting flows and distance.

[Figures OA B.1–OA B.5]

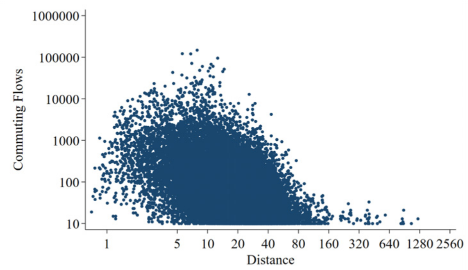


(a) Male (Age 15–29) (b) Male (Age 30–44) (c) Male (Age 45–59) (d) Male (Age ≥ 60)

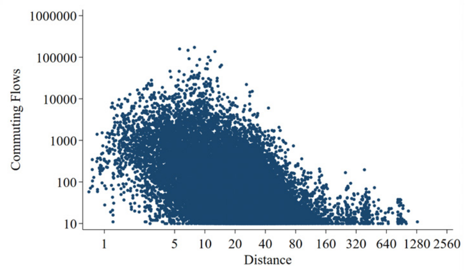
(e) Female (Age 15–29) (f) Female (Age 30–44) (g) Female (Age 45–59) (h) Female (Age ≥ 60)

Figure OA B.1: Scatterplot on Commuting Flows and Distance by Age Group in 2010

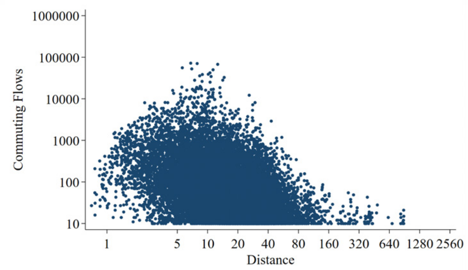
Note: Created by the author using the 2010 Population Census (Ministry of Internal Affairs and Communications). Inter-municipal commuting flows below 10 persons are not reported here.



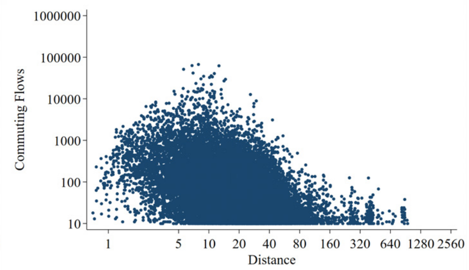
(a) Single male age ≤ 49



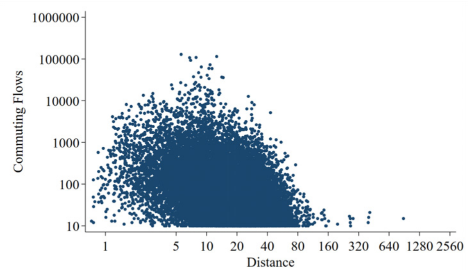
(b) Married male age ≤ 49
without children (age 0–15)



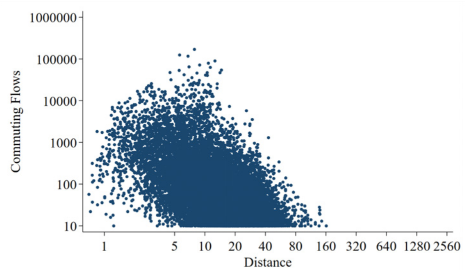
(c) Married male age ≤ 49
with children (age 0–5)



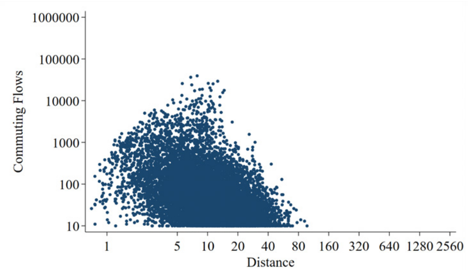
(d) [Married male age ≤ 49
with children (age 6–15)



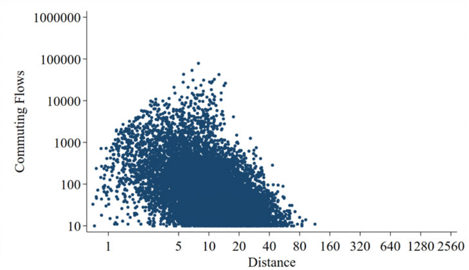
(e) Single female age ≤ 49



(f) Married female age ≤ 49
without children (age 0–15)



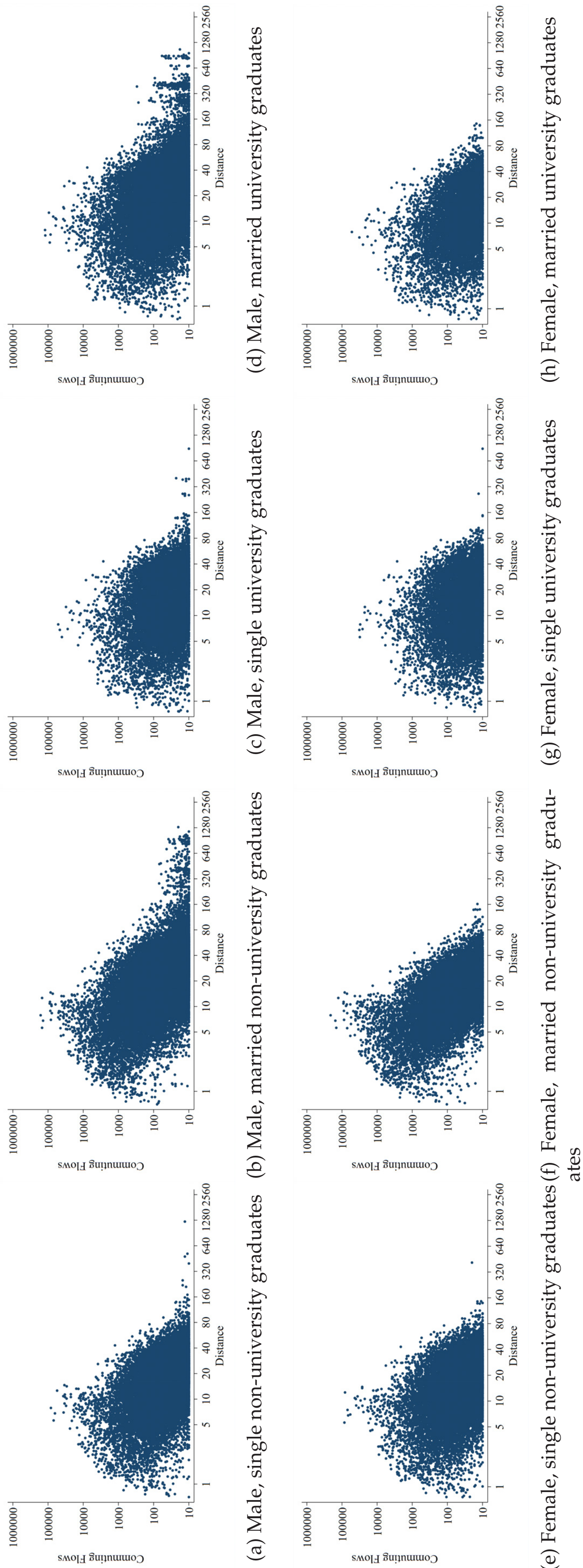
(g) Married female age ≤ 49
with children (age 0–5)



(h) Married female age ≤ 49
with children (age 6–15)

Figure OA B.2: Scatterplot on Commuting Flows and Distance by Marriage Status in 2010

Note: Created by the author using the 2010 Population Census (Ministry of Internal Affairs and Communications). Inter-municipal commuting flows below 10 persons are not reported here.



(a) Male, single non-university graduates

(b) Male, married non-university graduates

(c) Male, single university graduates

(d) Male, married university graduates

(e) Female, single non-university graduates

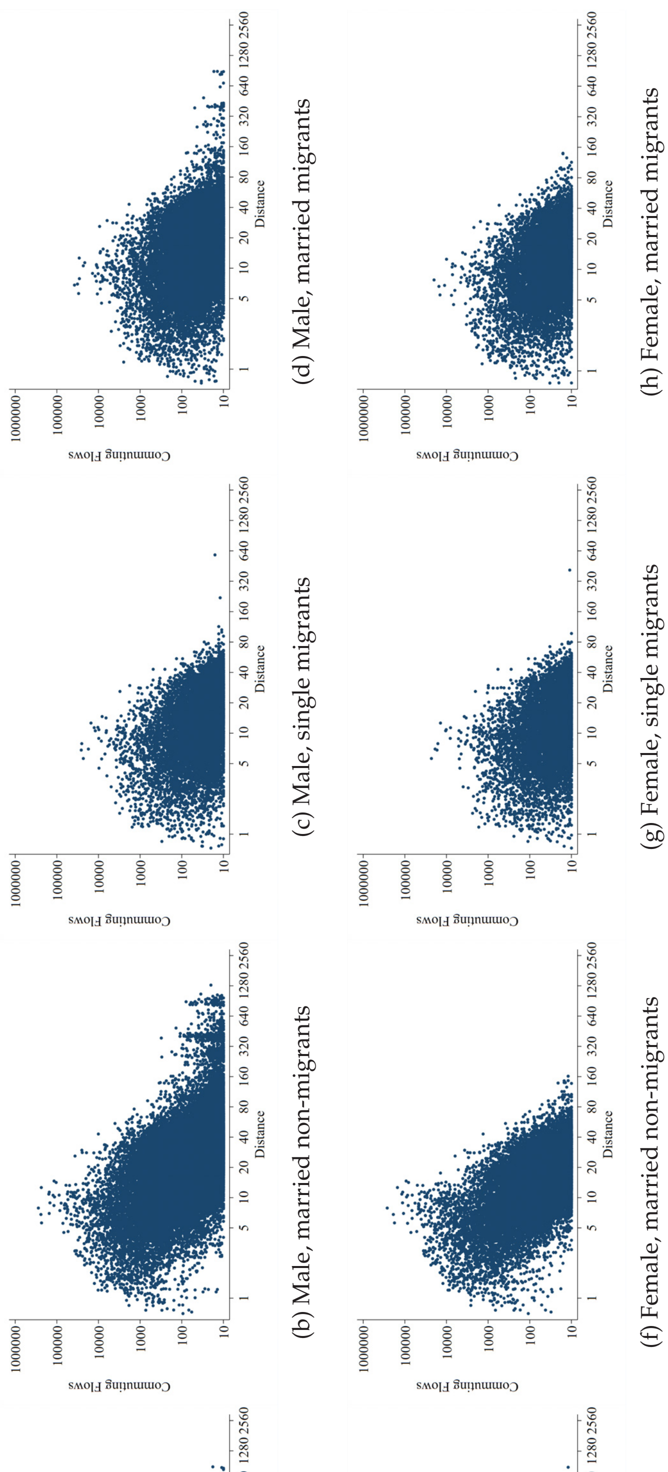
(f) Female, married non-university graduates

(g) Female, single university graduates

(h) Female, married university graduates

Figure OA B.3: Scatterplot on Commuting Flows and Distance by Education Group in 2010

Note: Created by the author using the 2010 Population Census (Ministry of Internal Affairs and Communications). Inter-municipal commuting flows below 10 persons are not reported here.



(a) Male, single non-migrants

(b) Male, married non-migrants

(c) Male, single migrants

(d) Male, married migrants

(e) Female, single non-migrants

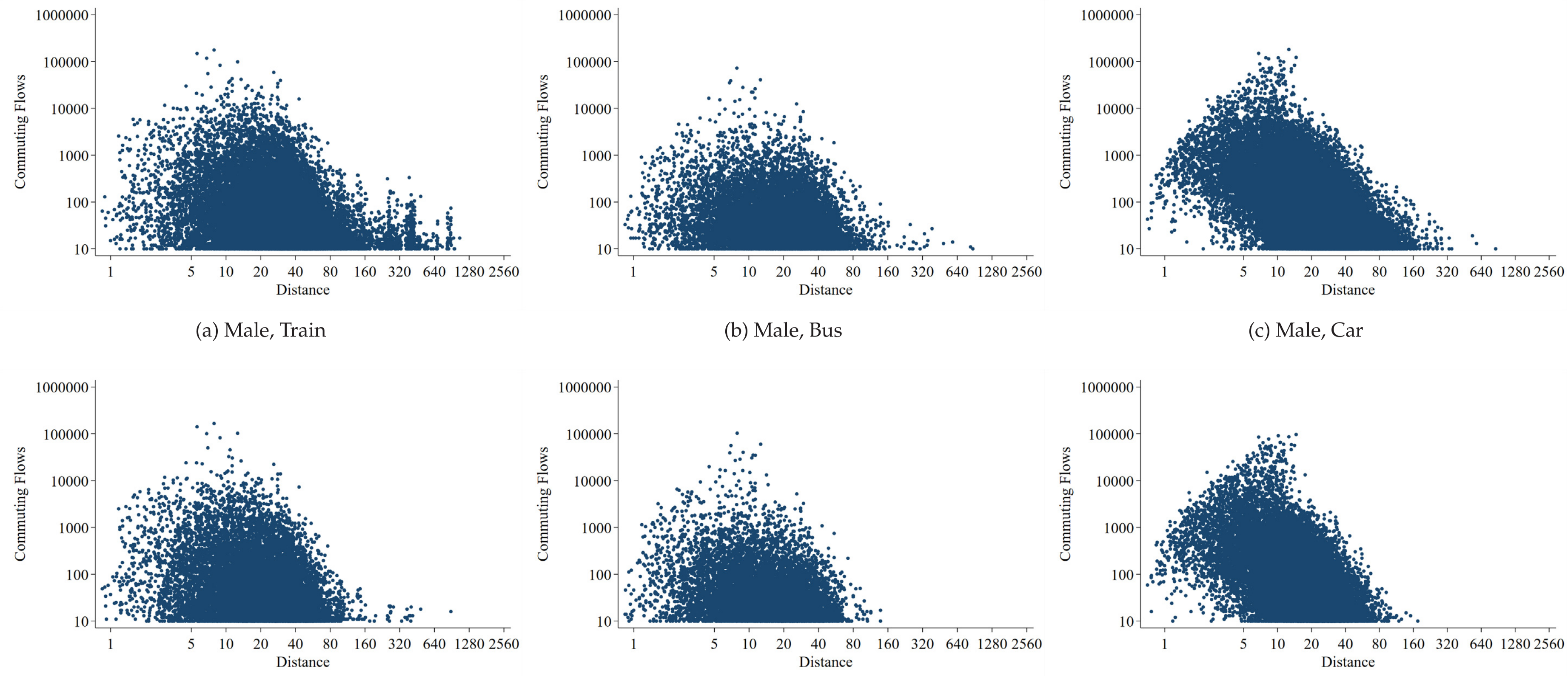
(f) Female, married non-migrants

(g) Female, single migrants

(h) Female, married migrants

Figure OA B.4: Scatterplot on Commuting Flows and Distance by Migration Experience in 2010

Note: Created by the author using the 2010 Population Census (Ministry of Internal Affairs and Communications). Inter-municipal commuting flows below 10 persons are not reported here.



(a) Male, Train

(b) Male, Bus

(c) Male, Car

(d) Female, Train

(e) Female, Bus

(f) Female, Car

Figure OA B.5: Scatterplot on Commuting Flows and Distance by Commuting Method in 2010

Note: Created by the author using the 2010 Population Census (Ministry of Internal Affairs and Communications). Inter-municipal commuting flows below 10 persons are not reported here.

Online Appendix C.

Estimation Results of Gravity Equation

Tables OA C.1–OA C.5 present estimation results of gravity equation of commuting by workers' characteristics, which correspond to Figures 3 and 6 in the paper.

[Tables OA C.1–OA C.5]

Table OA C.1 Estimation Results of Gravity Equation by Poisson Regression

	Dependent Variable: Inter-municipal Commuting Flows		
	Full Sample	Male	Female
Year	(1)	(2)	(3)
	Sample: Commuting across All Municipalities		
1980	3.217	2.987	3.817
	(0.0003)	(0.0003)	(0.0007)
1985	3.108	2.888	3.645
	(0.0003)	(0.0003)	(0.0006)
1990	3.007	2.804	3.475
	(0.0002)	(0.0003)	(0.0005)
1995	2.930	2.749	3.322
	(0.0002)	(0.0003)	(0.0005)
2000	2.887	2.713	3.241
	(0.0002)	(0.0003)	(0.0004)
2005	2.832	2.667	3.150
	(0.0002)	(0.0003)	(0.0004)
2010	2.791	2.631	3.078
	(0.0002)	(0.0003)	(0.0004)
2015	2.742	2.576	3.033
	(0.0002)	(0.0002)	(0.0004)
	Sample: Commuting to Tokyo's 23 Wards from Suburban Areas		
1980	2.942	2.833	3.504
	(0.0036)	(0.0040)	(0.0088)
1985	2.882	2.742	3.497
	(0.0034)	(0.0038)	(0.0080)
1990	2.757	2.590	3.371
	(0.0031)	(0.0035)	(0.0067)
1995	2.654	2.487	3.213
	(0.0029)	(0.0034)	(0.0062)
2000	2.574	2.394	3.135
	(0.0030)	(0.0034)	(0.0061)
2005	2.500	2.313	3.046
	(0.0030)	(0.0035)	(0.0060)
2010	2.403	2.206	2.930
	(0.0031)	(0.0036)	(0.0060)
2015	2.308	2.098	2.827
	(0.0030)	(0.0036)	(0.0058)

Note: Standard errors are in the parentheses. All regressions include origin and destination fixed effects. The number of municipality is 1,741 (as of October 1, 2015). Total commuting flows between all municipalities become 3,031,081 ($= 1,741 \times 1,741$) including commuting within municipalities. Commuting flows from municipalities in Greater Tokyo Area to Tokyo's 23 Wards become 7,360 ($= 320 \times 23$) excluding commuting across Tokyo's 23 Wards.

Table OA C.2 Estimation Results of Gravity Equation by Poisson Regression by Age Group

	Dependent Variable: Inter-municipal Commuting Flows							
	Male				Female			
	Age 15–29	Age 30–44	Age 45–59	Age ≥ 60	Age 15–29	Age 30–44	Age 45–59	Age ≥ 60
Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample: Commuting across All Municipalities							
1980	2.848	2.897	3.067	3.783	3.131	4.063	4.279	5.196
	(0.0006)	(0.0005)	(0.0006)	(0.0017)	(0.0009)	(0.0013)	(0.0016)	(0.0045)
1985	2.733	2.797	2.955	3.683	2.972	3.812	4.054	4.940
	(0.0006)	(0.0005)	(0.0006)	(0.0015)	(0.0008)	(0.0011)	(0.0014)	(0.0037)
1990	2.675	2.717	2.821	3.479	2.863	3.578	3.852	4.664
	(0.0006)	(0.0004)	(0.0005)	(0.0012)	(0.0008)	(0.0010)	(0.0011)	(0.0030)
1995	2.656	2.645	2.723	3.382	2.783	3.328	3.637	4.411
	(0.0005)	(0.0004)	(0.0004)	(0.0010)	(0.0007)	(0.0009)	(0.0009)	(0.0024)
2000	2.675	2.588	2.676	3.308	2.780	3.148	3.501	4.304
	(0.0006)	(0.0004)	(0.0004)	(0.0010)	(0.0007)	(0.0008)	(0.0008)	(0.0022)
2005	2.662	2.538	2.614	3.171	2.741	3.002	3.348	4.062
	(0.0006)	(0.0004)	(0.0004)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0018)
2010	2.637	2.518	2.554	3.029	2.696	2.918	3.215	3.812
	(0.0007)	(0.0004)	(0.0004)	(0.0007)	(0.0008)	(0.0006)	(0.0008)	(0.0015)
2015	2.608	2.487	2.452	2.939	2.672	2.884	3.098	3.669
	(0.0007)	(0.0004)	(0.0004)	(0.0007)	(0.0008)	(0.0006)	(0.0007)	(0.0013)
	Sample: Commuting to Tokyo's 23 Wards from Suburban Areas							
1980	2.708	2.896	2.909	2.642	3.433	3.609	3.600	3.367
	(0.0085)	(0.0057)	(0.0082)	(0.0188)	(0.0125)	(0.0170)	(0.0206)	(0.0497)
1985	2.641	2.733	2.902	2.586	3.347	3.669	3.663	3.280
	(0.0084)	(0.0056)	(0.0071)	(0.0172)	(0.0113)	(0.0155)	(0.0178)	(0.0424)
1990	2.557	2.493	2.780	2.597	3.200	3.473	3.689	3.275
	(0.0073)	(0.0056)	(0.0062)	(0.0138)	(0.0092)	(0.0138)	(0.0154)	(0.0344)
1995	2.466	2.336	2.643	2.643	3.036	3.160	3.635	3.287
	(0.0071)	(0.0057)	(0.0058)	(0.0119)	(0.0087)	(0.0126)	(0.0137)	(0.0290)
2000	2.387	2.252	2.489	2.744	2.907	3.043	3.634	3.433
	(0.0078)	(0.0056)	(0.0059)	(0.0116)	(0.0092)	(0.0112)	(0.0137)	(0.0280)
2005	2.276	2.206	2.335	2.768	2.740	2.942	3.547	3.517
	(0.0090)	(0.0054)	(0.0062)	(0.0107)	(0.0103)	(0.0097)	(0.0136)	(0.0250)
2010	2.179	2.113	2.156	2.634	2.605	2.798	3.343	3.532
	(0.0101)	(0.0056)	(0.0064)	(0.0096)	(0.0110)	(0.0094)	(0.0131)	(0.0219)
2015	2.078	2.019	2.009	2.535	2.443	2.721	3.115	3.493
	(0.0107)	(0.0059)	(0.0061)	(0.0094)	(0.0113)	(0.0092)	(0.0113)	(0.0208)

Note: Standard errors are in the parentheses. All regressions include origin and destination fixed effects. The number of municipality is 1,741 (as of October 1, 2015). Total commuting flows between all municipalities become 3,031,081 (= $1,741 \times 1,741$) including commuting within municipalities. Commuting flows from municipalities in Greater Tokyo Area to Tokyo's 23 Wards become 7,360 (= 320×23) excluding commuting across Tokyo's 23 Wards.

Table OA C.3 Estimation Results of Gravity Equation by Poisson Regression by Marriage Status

	Dependent Variable: Inter-municipal Commuting Flows							
	Male				Female			
	Single age ≤ 49	Married age ≤ 49			Single age ≤ 49	Married age ≤ 49		
	Full	No Child (Age 0–15)	with Children (Age 0–5)	with Children (Age 6–15)	Full	No Child (Age 0–15)	with Children (Age 0–5)	with Children (Age 6–15)
Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample: Commuting across All Municipalities							
1980	2.820	2.952	2.901	2.962	2.970	4.168	4.204	4.486
	(0.0006)	(0.0010)	(0.0007)	(0.0007)	(0.0010)	(0.0012)	(0.0024)	(0.0021)
1985	2.725	2.831	2.800	2.832	2.868	3.921	3.834	4.183
	(0.0006)	(0.0009)	(0.0007)	(0.0007)	(0.0008)	(0.0010)	(0.0020)	(0.0017)
1990	2.676	2.701	2.727	2.729	2.793	3.712	3.699	3.892
	(0.0005)	(0.0009)	(0.0006)	(0.0006)	(0.0007)	(0.0009)	(0.0017)	(0.0015)
1995	2.648	2.643	2.668	2.659	2.730	3.489	3.497	3.665
	(0.0005)	(0.0008)	(0.0006)	(0.0006)	(0.0007)	(0.0008)	(0.0016)	(0.0014)
2000	2.653	2.593	2.612	2.601	2.724	3.330	3.335	3.535
	(0.0005)	(0.0008)	(0.0006)	(0.0007)	(0.0007)	(0.0008)	(0.0015)	(0.0014)
2005	2.627	2.526	2.550	2.518	2.681	3.194	3.204	3.388
	(0.0005)	(0.0008)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0014)	(0.0013)
2010	2.610	2.483	2.504	2.471	2.645	3.091	3.093	3.296
	(0.0005)	(0.0008)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0014)	(0.0013)
2015	2.594	2.448	2.445	2.397	2.627	3.038	3.026	3.238
	(0.0005)	(0.0008)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0013)	(0.0012)
	Sample: Commuting to Tokyo's 23 Wards from Suburban Areas							
1980	2.675	2.771	2.857	3.055	3.365	3.449	3.950	4.133
	(0.0087)	(0.0118)	(0.0079)	(0.0082)	(0.0123)	(0.0220)	(0.0381)	(0.0320)
1985	2.629	2.722	2.667	2.921	3.315	3.497	3.774	4.192
	(0.0080)	(0.0116)	(0.0083)	(0.0080)	(0.0110)	(0.0213)	(0.0343)	(0.0280)
1990	2.520	2.530	2.511	2.645	3.168	3.362	3.749	4.106
	(0.0068)	(0.0104)	(0.0082)	(0.0083)	(0.0090)	(0.0185)	(0.0318)	(0.0255)
1995	2.413	2.372	2.406	2.417	2.985	3.165	3.627	3.921
	(0.0063)	(0.0095)	(0.0085)	(0.0090)	(0.0083)	(0.0162)	(0.0322)	(0.0269)
2000	2.321	2.258	2.312	2.288	2.859	3.031	3.425	4.012
	(0.0066)	(0.0099)	(0.0087)	(0.0101)	(0.0083)	(0.0157)	(0.0306)	(0.0296)
2005	2.249	2.160	2.228	2.195	2.724	2.899	3.306	3.756
	(0.0069)	(0.0101)	(0.0088)	(0.0103)	(0.0085)	(0.0154)	(0.0279)	(0.0273)
2010	2.189	2.075	2.088	2.037	2.606	2.774	2.959	3.644
	(0.0073)	(0.0104)	(0.0090)	(0.0102)	(0.0086)	(0.0153)	(0.0244)	(0.0266)
2015	2.102	1.983	1.974	1.941	2.494	2.674	2.815	3.402
	(0.0075)	(0.0109)	(0.0092)	(0.0103)	(0.0086)	(0.0153)	(0.0207)	(0.0239)

Note: Standard errors are in the parentheses. All regressions include origin and destination fixed effects. The number of municipality is 1,741 (as of October 1, 2015). Total commuting flows between all municipalities become 3,031,081 (= $1,741 \times 1,741$) including commuting within municipalities. Commuting flows from municipalities in Greater Tokyo Area to Tokyo's 23 Wards become 7,360 (= 320×23) excluding commuting across Tokyo's 23 Wards.

Table OA C.4 Estimation Results of Gravity Equation by Poisson Regression by Education

	Dependent Variable: Inter-municipal Commuting Flows							
	Male				Female			
	Non-Univ. Graduates		University Graduates		Non-Univ. Graduates		University Graduates	
	Single	Married	Single	Married	Single	Married	Single	Married
Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample: Commuting across All Municipalities							
1980	2.934	3.147	2.478	2.509	3.035	4.402	2.492	2.948
	(0.0008)	(0.0004)	(0.0012)	(0.0008)	(0.0010)	(0.0012)	(0.0025)	(0.0031)
1985								
1990	2.778	2.969	2.397	2.460	2.863	3.973	2.393	2.898
	(0.0006)	(0.0004)	(0.0010)	(0.0006)	(0.0008)	(0.0009)	(0.0019)	(0.0021)
1995								
2000	2.751	2.857	2.421	2.411	2.809	3.632	2.416	2.819
	(0.0006)	(0.0004)	(0.0009)	(0.0005)	(0.0007)	(0.0007)	(0.0013)	(0.0015)
2005								
2010	2.730	2.765	2.410	2.362	2.773	3.410	2.373	2.729
	(0.0007)	(0.0004)	(0.0008)	(0.0005)	(0.0008)	(0.0007)	(0.0011)	(0.0012)
2015								
	Sample: Commuting to Tokyo's 23 Wards from Suburban Areas							
1980	2.854	3.073	2.311	2.492	3.448	3.781	2.613	3.248
	(0.0110)	(0.0056)	(0.0146)	(0.0079)	(0.0131)	(0.0158)	(0.0334)	(0.0388)
1985								
1990	2.727	2.843	2.198	2.299	3.316	3.790	2.296	3.041
	(0.0089)	(0.0055)	(0.0107)	(0.0066)	(0.0099)	(0.0131)	(0.0216)	(0.0262)
1995								
2000	2.565	2.707	2.033	2.080	3.070	3.647	2.271	2.851
	(0.0089)	(0.0060)	(0.0096)	(0.0061)	(0.0099)	(0.0125)	(0.0154)	(0.0201)
2005								
2010	2.455	2.509	1.960	1.902	2.896	3.514	2.213	2.623
	(0.0105)	(0.0068)	(0.0098)	(0.0060)	(0.0114)	(0.0128)	(0.0129)	(0.0161)
2015								

Note: Standard errors are in the parentheses. All regressions include origin and destination fixed effects. The number of municipality is 1,741 (as of October 1, 2015). Total commuting flows between all municipalities become 3,031,081 (= $1,741 \times 1,741$) including commuting within municipalities. Commuting flows from municipalities in Greater Tokyo Area to Tokyo's 23 Wards become 7,360 (= 320×23) excluding commuting across Tokyo's 23 Wards.

Table OA C.5 Estimation Results of Gravity Equation by Poisson Regression by Migration Experience

	Dependent Variable: Inter-municipal Commuting Flows							
	Male				Female			
	Non-Migrants		Migrants		Non-Migrants		Migrants	
	Single	Married	Single	Married	Single	Married	Single	Married
Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample: Commuting across All Municipalities							
1980	2.829	3.136	2.825	2.570	3.015	4.616	2.882	3.174
	(0.0007)	(0.0004)	(0.0013)	(0.0008)	(0.0011)	(0.0014)	(0.0020)	(0.0018)
1985								
1990	2.659	2.910	2.751	2.487	2.815	4.049	2.755	2.935
	(0.0006)	(0.0004)	(0.0011)	(0.0008)	(0.0008)	(0.0009)	(0.0017)	(0.0016)
1995								
2000	2.648	2.788	2.705	2.405	2.748	3.685	2.661	2.718
	(0.0005)	(0.0003)	(0.0011)	(0.0007)	(0.0007)	(0.0008)	(0.0015)	(0.0013)
2005								
2010	2.605	2.669	2.698	2.346	2.664	3.409	2.593	2.576
	(0.0005)	(0.0003)	(0.0012)	(0.0008)	(0.0007)	(0.0007)	(0.0015)	(0.0013)
2015	2.585	2.591	2.714	2.298	2.645	3.325	2.603	2.556
	(0.0005)	(0.0003)	(0.0013)	(0.0008)	(0.0007)	(0.0006)	(0.0016)	(0.0012)
	Sample: Commuting to Tokyo's 23 Wards from Suburban Areas							
1980	2.639	2.980	2.759	2.727	3.387	3.914	3.236	3.466
	(0.0113)	(0.0057)	(0.0137)	(0.0076)	(0.0146)	(0.0202)	(0.0214)	(0.0212)
1985								
1990	2.497	2.711	2.620	2.416	3.245	3.913	2.897	3.210
	(0.0086)	(0.0049)	(0.0111)	(0.0081)	(0.0103)	(0.0147)	(0.0173)	(0.0189)
1995								
2000	2.341	2.476	2.367	2.261	2.884	3.696	2.762	3.013
	(0.0078)	(0.0049)	(0.0116)	(0.0083)	(0.0093)	(0.0131)	(0.0173)	(0.0176)
2005								
2010	2.183	2.231	2.324	2.074	2.600	3.442	2.668	2.687
	(0.0081)	(0.0049)	(0.0138)	(0.0092)	(0.0094)	(0.0117)	(0.0181)	(0.0175)
2015	2.087	2.094	2.313	1.980	2.470	3.248	2.659	2.586
	(0.0080)	(0.0048)	(0.0150)	(0.0100)	(0.0092)	(0.0106)	(0.0187)	(0.0173)

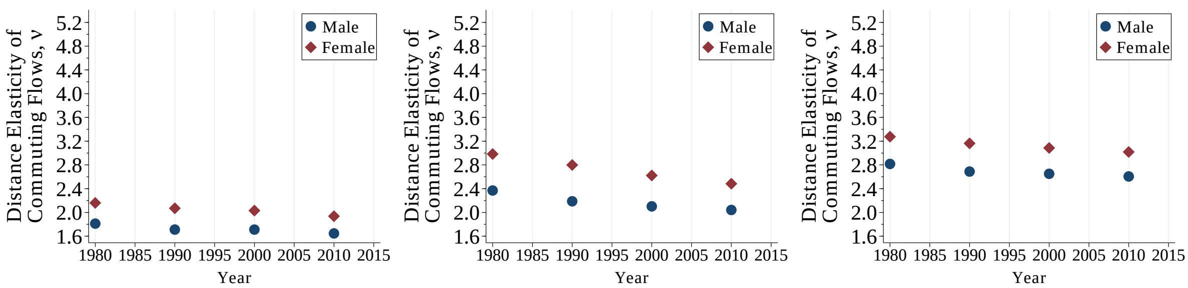
Note: Standard errors are in the parentheses. All regressions include origin and destination fixed effects. The number of municipality is 1,741 (as of October 1, 2015). Total commuting flows between all municipalities become 3,031,081 (= $1,741 \times 1,741$) including commuting within municipalities. Commuting flows from municipalities in Greater Tokyo Area to Tokyo's 23 Wards become 7,360 (= 320×23) excluding commuting across Tokyo's 23 Wards.

Online Appendix D.

Estimation Results of Gravity Equation by Commuting Method

Figures OA D.1–OA D.2 present estimation results of gravity equation of commuting by commuting method. Table OA D.1 provides numerical details of the estimation results.

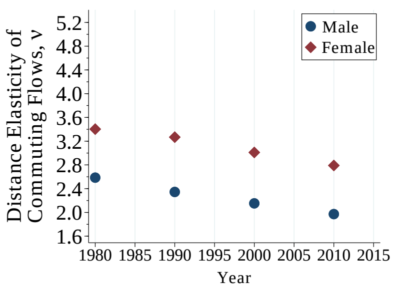
[Figures OA D.1–OA D.2; Table OA D.1]



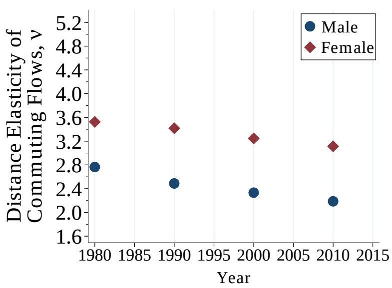
(a) Train (b) Bus (c) Car

Figure OA D.1: Distance Elasticity of Commuting Flows Estimated by Commuting across All Municipalities (by Commuting Method)

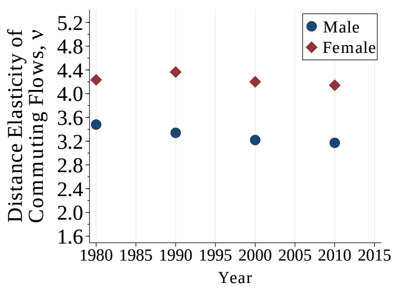
Note: Estimated by the Poisson regression with origin and destination fixed dummies. Commuting method information is not available in the 1985, 1995, 2005, and 2015 Population Censuses (Ministry of Internal Affairs and Communications).



(a) Train



(b) Bus



(c) Car

Figure OA D.2: Distance Elasticity of Commuting Flows Estimated from Data on Commuting to Tokyo's 23 Wards from Suburban Areas (by Commuting Method)

Note: Estimated by the Poisson regression with origin and destination fixed dummies. Commuting method information is not available in the 1985, 1995, 2005, and 2015 Population Censuses (Ministry of Internal Affairs and Communications).

Table OA D.1 Estimation Results of Gravity Equation by Poisson Regression by Commuting Method

	Dependent Variable: Inter-municipal Commuting Flows					
	Male			Female		
	Train	Bus	Car	Train	Bus	Car
Year	(1)	(2)	(3)	(4)	(5)	(6)
	Sample: Commuting across All Municipalities					
1980	1.811	2.369	2.817	2.160	2.984	3.276
	(0.0005)	(0.0007)	(0.0005)	(0.0008)	(0.0011)	(0.0014)
1985						
1990	1.711	2.188	2.688	2.070	2.799	3.163
	(0.0005)	(0.0008)	(0.0004)	(0.0007)	(0.0011)	(0.0008)
1995						
2000	1.711	2.102	2.651	2.031	2.622	3.086
	(0.0005)	(0.0008)	(0.0003)	(0.0007)	(0.0011)	(0.0006)
2005						
2010	1.646	2.041	2.606	1.936	2.483	3.018
	(0.0005)	(0.0009)	(0.0003)	(0.0006)	(0.0012)	(0.0005)
2015						
	Sample: Commuting to Tokyo's 23 Wards from Suburban Areas					
1980	2.586	2.765	3.479	3.403	3.526	4.234
	(0.0044)	(0.0076)	(0.0095)	(0.0091)	(0.0146)	(0.0407)
1985						
1990	2.345	2.488	3.340	3.268	3.418	4.364
	(0.0039)	(0.0073)	(0.0084)	(0.0069)	(0.0122)	(0.0292)
1995						
2000	2.153	2.333	3.219	3.010	3.247	4.200
	(0.0038)	(0.0079)	(0.0088)	(0.0063)	(0.0124)	(0.0265)
2005						
2010	1.972	2.187	3.172	2.791	3.113	4.142
	(0.0039)	(0.0089)	(0.0110)	(0.0062)	(0.0135)	(0.0302)
2015						

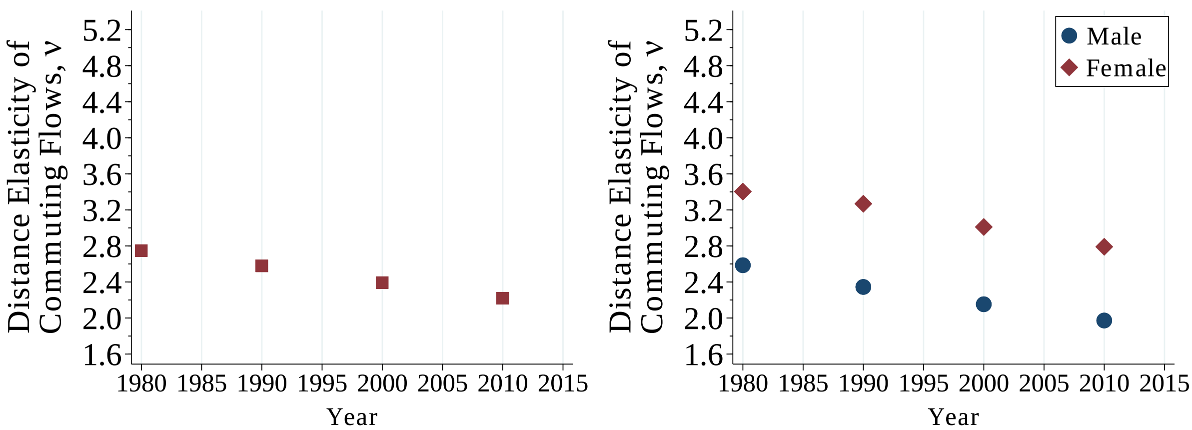
Note: Standard errors are in the parentheses. Origin and destination fixed effects are included, but not report. The number of municipality Note: Standard errors are in the parentheses. All regressions include origin and destination fixed effects. The number of municipality is 1,741 (as of October 1, 2015). Total commuting flows between all municipalities become 3,031,081 (= $1,741 \times 1,741$) including commuting within municipalities. Commuting flows from municipalities in Greater Tokyo Area to Tokyo's 23 Wards become 7,360 (= 320×23) excluding commuting across Tokyo's 23 Wards.

Online Appendix E.

Distance Elasticity of Commuting (Commuting to Tokyo's 23 Wards by Train)

Figures OA E.1–OA E.2 present estimation results of gravity equation estimated from data on commuting to Tokyo's 23 Wards by train.

[Figures OA E.1–OA E.2]

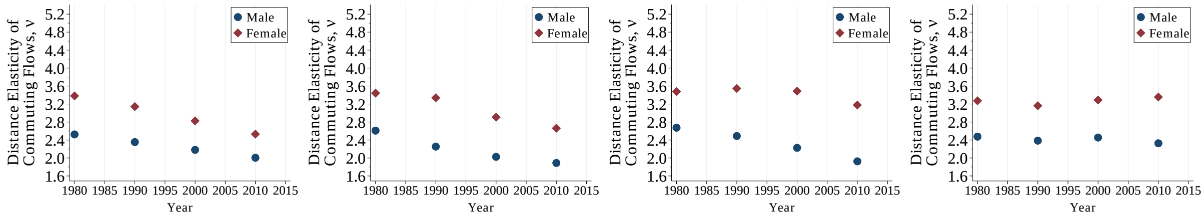


(a) Full Sample

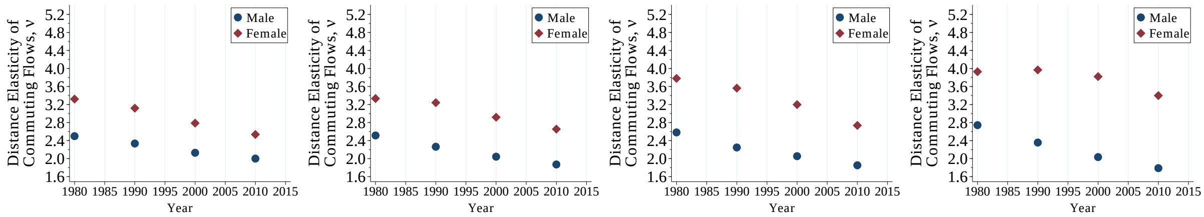
(b) Sample by Gender

Figure OA E.1: Distance Elasticity of Commuting Flows Estimated from Data on Commuting to Tokyo's 23 Wards from Suburban Areas (Commuting by Train)

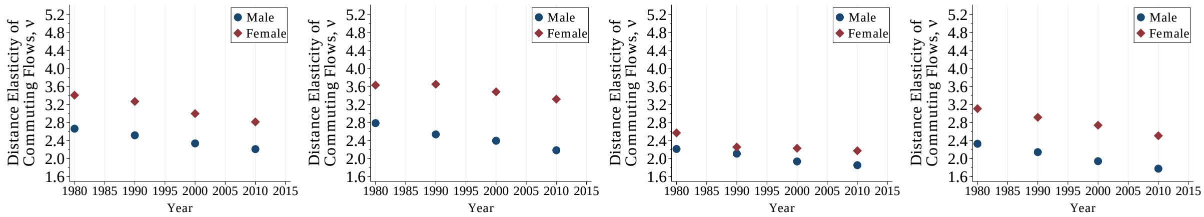
Note: Estimated by the Poisson regression with origin and destination fixed dummies.



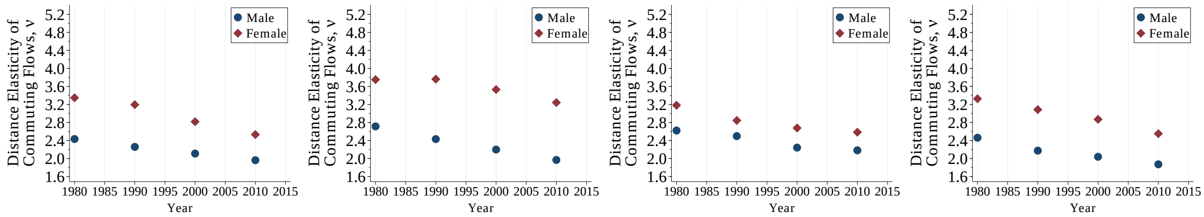
(a) Age 15–29 (b) Age 30–44 (c) Age 45–59 (d) Age 60 and above



(e) Single age ≤ 49 (f) Married age ≤ 49 without children (age 0–15) (g) Married age ≤ 49 with children (age 0–5) (h) Married age ≤ 49 with children (age 6–15)



(i) Single non-university graduates (j) Married non-university graduates (k) Single university graduates (l) Married university graduates



(m) Single non-migrants (n) Married non-migrants (o) Single migrants (p) Married migrants

Figure OA E.2: Heterogeneity in Distance Elasticity of Commuting Flows Estimated from Data on Commuting to Tokyo's 23 Wards from Suburban Areas (Commuting by Train)

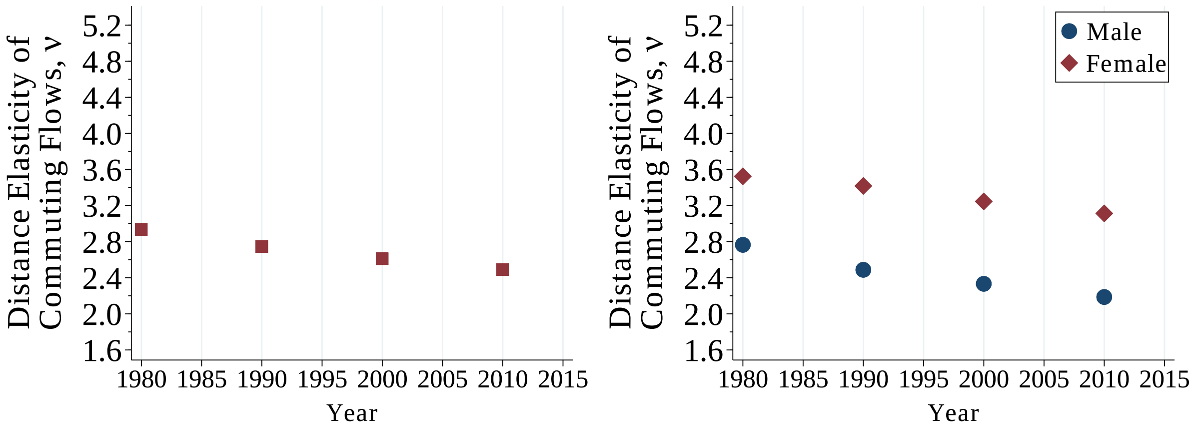
Note: Estimated by the Poisson regression with origin and destination fixed dummies. Education information is not available in the 1985, 1995, 2005, and 2015 Population Censuses (Ministry of Internal Affairs and Communications); migration information is not available in the 1985, 1995, and 2005 Population Censuses (Ministry of Internal Affairs and Communications).

Online Appendix F.

Distance Elasticity of Commuting (Commuting to Tokyo's 23 Wards by Bus)

Figures OA F.1–OA F.2 present estimation results of gravity equation estimated from data on commuting to Tokyo's 23 Wards by bus.

[Figures OA F.1–OA F.2]

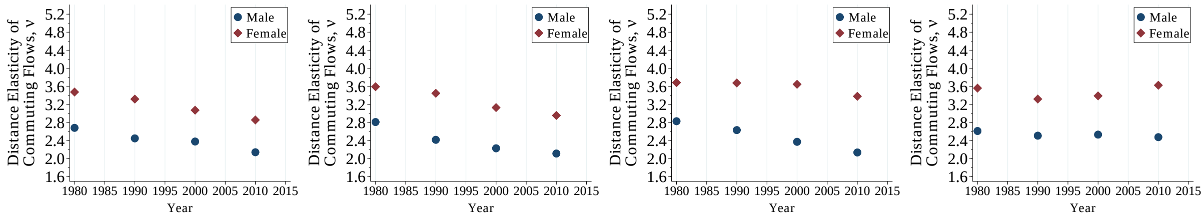


(a) Full Sample

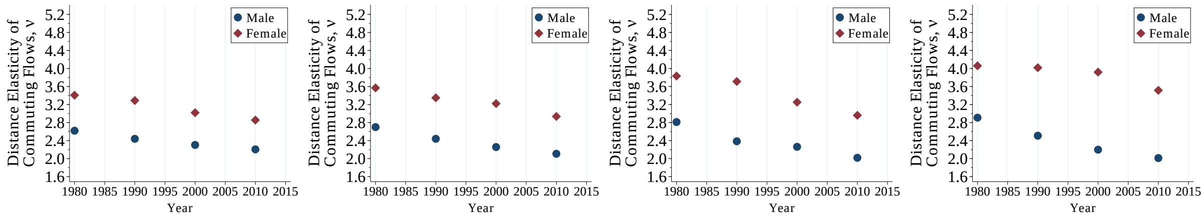
(b) Sample by Gender

Figure OA F.1: Distance Elasticity of Commuting Flows Estimated from Data on Commuting to Tokyo's 23 Wards from Suburban Areas (Commuting by Bus)

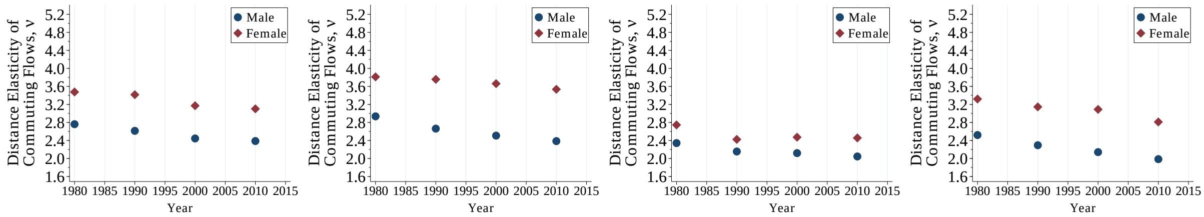
Note: Estimated by the Poisson regression with origin and destination fixed dummies.



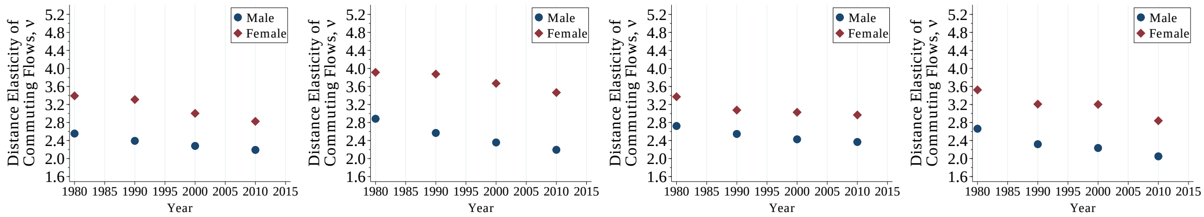
(a) Age 15–29 (b) Age 30–44 (c) Age 45–59 (d) Age 60 and above



(e) Single aged less than 49 (f) Married age ≤ 49 (g) Married age ≤ 49 with children (age 0–5) (h) Married age ≤ 49 with children (age 6–15)



(i) Single non-university graduates (j) Married non-university graduates (k) Single university graduates (l) Married university graduates



(m) Single non-migrants (n) Married non-migrants (o) Single migrants (p) Married migrants

Figure OA F.2: Heterogeneity in Distance Elasticity of Commuting Flows Estimated from Data on Commuting to Tokyo's 23 Wards from Suburban Areas (Commuting by Bus)

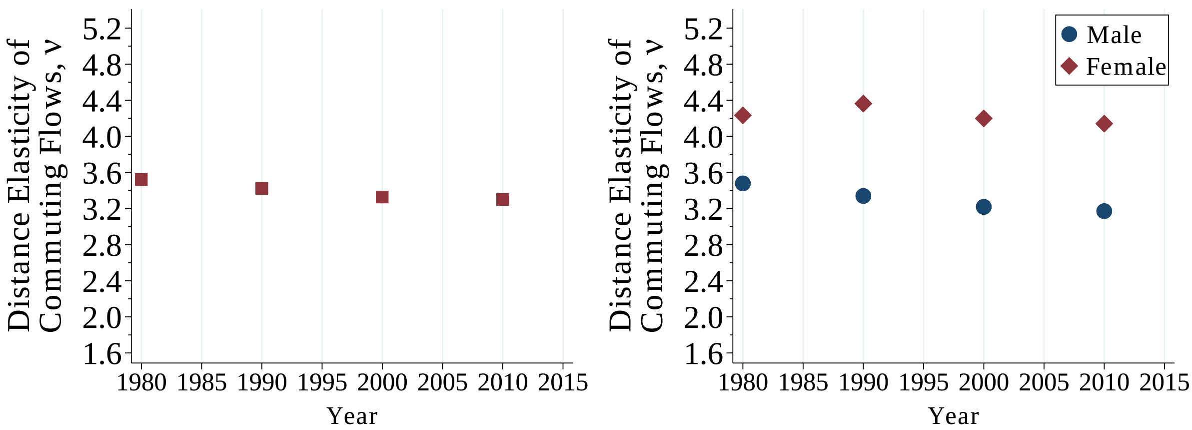
Note: Estimated by the Poisson regression with origin and destination fixed dummies. Education information is not available in the 1985, 1995, 2005, and 2015 Population Censuses (Ministry of Internal Affairs and Communications); migration information is not available in the 1985, 1995, and 2005 Population Censuses (Ministry of Internal Affairs and Communications).

Online Appendix G.

Distance Elasticity of Commuting (Commuting to Tokyo's 23 Wards by Car)

Figures OA G.1–OA G.2 present estimation results of gravity equation estimated from data on commuting to Tokyo's 23 Wards by car.

[Figures OA G.1–OA G.2]

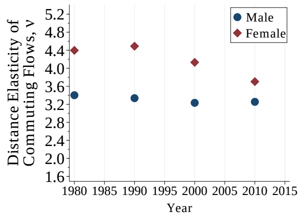


(a) Full Sample

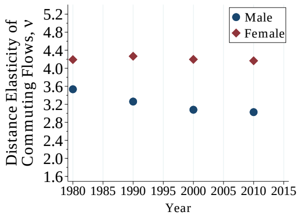
(b) Sample by Gender

Figure OA G.1: Distance Elasticity of Commuting Flows Estimated from Data on Commuting to Tokyo's 23 Wards from Suburban Areas (Commuting by Car)

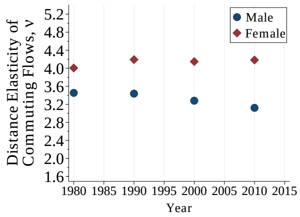
Note: Estimated by the Poisson regression with origin and destination fixed dummies.



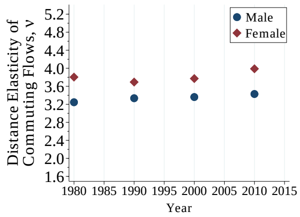
(a) Age 15–29



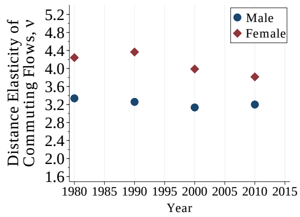
(b) Age 30–44



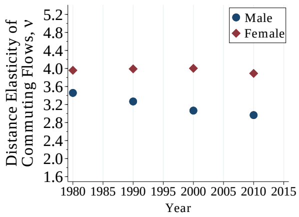
(c) Age 45–59



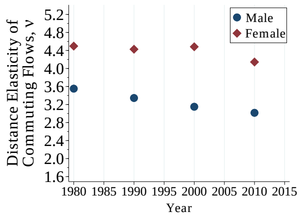
(d) Age 60 and above



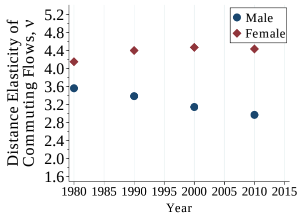
(e) Single age ≤ 49



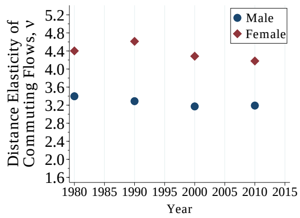
(f) Married age ≤ 49
without children (age 0–15)



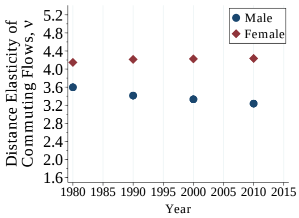
(g) Married age ≤ 49
with children (age 0–5)



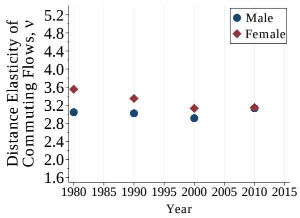
(h) Married age ≤ 49
with children (age 6–15)



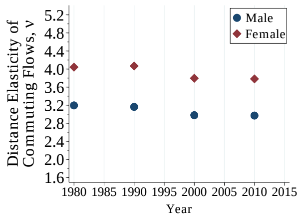
(i) Single
non-university graduates



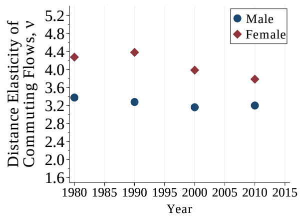
(j) Married
non-university graduates



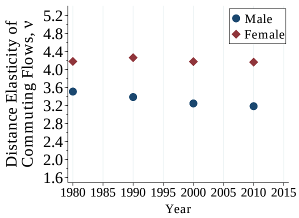
(k) Single
university graduates



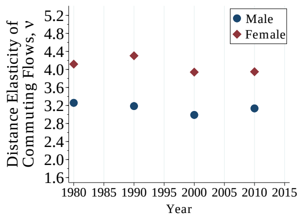
(l) Married
university graduates



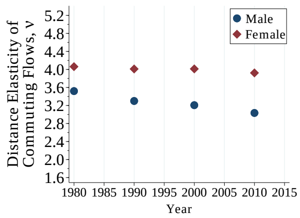
(m) Single
non-migrants



(n) Married
non-migrants



(o) Single migrants



(p) Married migrants

Figure OA G.2: Heterogeneity in Distance Elasticity of Commuting Flows Estimated from Data on Commuting to Tokyo's 23 Wards from Suburban Areas (Commuting by Car)

Note: Estimated by the Poisson regression with origin and destination fixed dummies. Education information is not available in the 1985, 1995, 2005, and 2015 Population Censuses (Ministry of Internal Affairs and Communications); migration information is not available in the 1985, 1995, and 2005 Population Censuses (Ministry of Internal Affairs and Communications).