The Geography of Jobs and the Gender Wage Gap

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Abstract

Prior studies have shown that gender differences in commuting preferences can lead women to give up higher wages in exchange for a short commute than men, indicating that spatial commuting friction could potentially exacerbate the gender wage gap. We study how much the spatial distribution of jobs and workers affects commuting friction and contributes to the gender wage gap. We first document that the gender wage gap is considerably smaller for workers living closer to the central city, where many high-paying jobs are concentrated. Then, we develop a job choice model to analyze the role of commuting preferences and commuting friction. Using data from the American Community Survey, the Zip Code Business Patterns, and a travel time matrix that we compute, we estimate (1) the slope of indifference curves between wage and commute time with a lower-envelope estimator using data on the observed job bundles chosen by workers, and (2) the wage return to commuting faced by each worker with an upper-envelope estimator using data on the spatial distribution of jobs faced by the worker. Based on the estimates and the job choice model, we find that given the distribution of jobs and workers, the gender difference in commuting preferences accounts for 33% of the observed gender wage gap. Reducing commute time by 10% (e.g., through improved transportation) can lower the gender wage gap by 2.4%. [Results are preliminary and subject to changes.]

Keywords: Gender wage gap, commuting, spatial distribution of jobs
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1 Introduction

Increased attention has been paid to how gender differences in preferences for non-wage job attributes, such as temporal flexibility and remote working arrangements, affect the gender wage gap (Bertrand et al., 2010; Goldin and Katz, 2011; Goldin, 2014; Blau and Kahn, 2017; Mas and Pallais, 2017; Wiswall and Zafar, 2017; Wasserman, 2019). Recent studies by Gutierrez (2018) and Le Barbanchon et al. (2019) have shown that gender differences in commuting preferences can lead women to give up higher wages than men in exchange for a short commute, resulting in a gender wage gap. This finding highlights that the commuting friction between jobs and workers can potentially be an important force that lowers women's relative wages.

The magnitude of commuting friction faced by workers is likely to differ by city and across neighborhoods within cities determined by the spatial distribution of jobs and workers' residential locations. Intuitively, if high-paying jobs are located near workers' residential locations, commuting preferences may not play an important role in affecting workers' job choices because workers of neither genders face a trade-off between higher wages and shorter commutes. In contrast, if high-paying jobs are located far away from workers' residential locations, workers face a trade-off between wages and commutes, in which case women could be more likely to give up far-away high-paying jobs for shorter commutes. Therefore, differential commuting preferences alone are not sufficient in explaining gender differences in commuting and wage outcomes: The magnitude of commuting friction faced by workers resulting from the geography of jobs could be an important determinant of the gender wage gap.

In this paper, we study how much the spatial distribution of jobs and workers contributes to the gender wage gap, given gender differences in commuting preferences. The goal is to understand the extent to which reducing spatial commuting friction can close the gender wage gap. To capture how commuting preferences and the geography of jobs jointly affect the gender wage gap, we present a job choice model in which workers trade off between wages and commute time, given their residential locations. Depending on the location of jobs, workers of different residential locations face different job choice sets, defined with a two-dimensional wage and commute space. The wage return to commuting is high (low) for workers living far away from (close to) high-paying jobs.[1] The model

[1]The wage return to commuting measures how much a worker's wage can increase by choosing to commute longer. If high-paying jobs are nearby, then the wage return to commuting would be low or even negative.

shows that, given the gender difference in commuting preferences, higher wage returns to commuting lead men to take high-paying jobs with long commutes more than women do, resulting in larger gender gaps in both commutes and wages.

Consistent with the prediction of the model, we empirically document that there is substantial variation in the gender commuting and wage gaps across locations within cities. In particular, the gaps are typically smaller for workers living in the central city, where many high-paying jobs are located. In contrast, the gaps tend to be larger for workers living in the suburbs.

Motivated by the descriptive evidence, we first estimate the key model parameters: (1) gender-specific preferences for commuting and (2) the wage return to commuting faced by each worker. Using the estimates and a structural framework provided by the job choice model, we quantify how much the spatial distribution of jobs and gender differences in commuting preferences contribute to the observed gender gaps in commutes and wages.

We estimate the marginal disutility of commuting for men and women separately by tracing out the slope of indifference curves between wage and commute time using micro-data from the American Community Survey (ACS). Exploiting the theoretical prediction that all the observed job bundles chosen by workers should be above the indifference curve associated with workers' reservation utility (in short, reservation curve), we construct a lower-envelope estimator to estimate the slope of the reservation curve using a nonparametric frontier estimator proposed by Cazals et al. (2002).[2] Consistent with prior studies, we find that women have stronger disutility of commuting. On average, women are willing to give up 39% of wages in exchange for a 1-hour shorter one-way commute, compared with 30% for men. The gender difference in commuting preferences is particularly pronounced among married workers and workers with children. Moreover, we find such gender differences in commuting preferences for every sub-population by skill, occupation, race, age, and the number of children. Similar results are also found across large metropolitan statistical areas (MSAs) and in every robustness test.

We measure the wage return to commuting faced by each worker using data on the spatial distribution of jobs and wages from the ACS and the Zip Code Business Patterns. For each residential location and occupation, we simulate available jobs and wages according to the implied spatial distributions from the data. Based on the simulated job choice set for each occupation and residential

[2]The results are robust to using alternative methods, including the estimator proposed by Le Barbanchon et al. (2019) and quantile regressions.

location, we construct an upper-envelope estimator to measure the wage return to commuting. We find that there is substantial variation in the wage return to commuting across occupations and residential locations in different MSAs. For instance, in the New York MSA, on average, increasing commute time by 10% is associated with an increase in the best expected wage offer by 2.8%.

Based on the estimates and the job choice model, we show that the predicted gender gaps in commute time by residential locations are strongly correlated with the observed gaps. We find that gender differences in commuting preferences contribute to 33.7% of the gender wage gap, given the spatial distribution of jobs and workers. Moreover, the effect of commuting preferences on the gender wage gap varies considerably by workers' residential locations. For instance, in the New York MSA, commuting preferences account for 36.7% (26.7%) of the gender wage gap for workers living 15-30 km (more than 30 km) away from downtown. However, for workers living within 5 km (5-15 km) away from downtown, commuting preferences can only account for 18.2% (11.6%) of the gender wage gap. The results suggest that reducing the remoteness to jobs may help reduce the gender wage gap, given gender differences in commuting preferences. More concretely, we show that reducing commute time between workers and jobs by 10% (e.g., through improving transportation) could decrease the overall gender wage gap by 2.4%. This indicates a potential benefit of more compact urban structures of jobs and workers.

A large body of literature has assessed the contributing factors behind the gender wage gap (Blau and Kahn, 2017). Since the 1980s, the traditional human capital factors have been less important in explaining the gender wage gap due to the reversal of the educational gap and the narrowing of the experience gap between men and women. Other contributing factors include the division of labor (Becker, 1985), gender differences in preferences for job flexibility (Cha and Weeden, 2014; Goldin, 2014), and the coordination of work schedule (Cubas et al., 2019) have drawn increasing attention. In addition, our work is also related to the recent studies that assess how preferences for non-wage job attributes affect the equilibrium job outcomes by gender. For instance, Mas and Pallais (2017) investigate how workers value alternative work arrangements and they find that women have higher willingness-to-pay to work at home. Similarly, Wiswall and Zafar (2017) find that women have stronger preferences for workplace flexibility. In contrast, men are found to have stronger preferences for future earning growths (Goldin and Katz, 2011; Bloom et al., 2015).

Within this strand of literature, Gutierrez (2018) and Le Barbanchon et al. (2019) are most related to our paper. To the best of our knowledge, Gutierrez (2018) is the first paper that documents gender differences in commuting patterns in the U.S. using the ACS and relates such differences to the earning disparities between husband and wife. His study focuses on identifying the importance of intra-household division of tasks within the context of a stylized model of city structure. Le Barbanchon et al. (2019) use French administrative data on job search criteria among unemployed workers to estimate their willingness-to-pay for shorter commutes. They use the stated reservation wage and maximum acceptable commute to make inference on workers' indifference curves between wages and commute time corresponding to the reservation utility.

The main difference between our paper and the aforementioned studies is that we focus how the geography of jobs and workers affect the gender commuting and wage gaps, given gender differences in commuting preferences. In particular, we show that differential gender preferences for commutes do not necessarily lead to gender wage gaps if the wage return to commuting is low (or negative). The key insight of our paper is that it is the *combination* of commuting preferences and the spatial distribution of wages that determines the gender wage gap.

Lastly, we contribute to the understanding of the linkages between spatial activities, transportation, and labor market outcomes (Becker, 1965; Small et al., 2005; Small and Verhoef, 2007; Ahlfeldt et al., 2015; Kreindler, 2018; Monte et al., 2018; Severen, 2019; Tsivanidis, 2019). The urban economics literature has explored the cost of commuting and the cost of spatial distance between jobs and workers. Our paper suggests another cost of commuting: People may give up high-paying jobs for shorter commutes. Moreover, the cost is higher for women than for men. Our results suggest that the decentralization of jobs or residential housing could not only increase the costs of commuting in general, but also exaggerate the gender wage inequality.

The rest of the paper is organized as follows. Section 2 describes the model. Section 3 describes the data and provides descriptive facts. The estimation strategy of the model parameters is outlined in Section 4. Results are presented and discussed in Section 5. Section 6 presents counterfactual analysis and Section 7 concludes.

[Note: The results mentioned in the introduction are still preliminary and subject to changes.]

2 Model

We present a simple job choice model to illustrate a potential source of geographic differences in the gender wage gap—the spatial distribution of jobs. Workers have preferences over a residential location-specific choice set of jobs, given their residential locations. A job is characterized with wages and commute time, and commute time is determined by the residential location of a worker and the location of the job. We assume that commuting preferences differ by gender. We then analyze how gender differences in commuting preferences affect gender differences in wages and commute time, and how the spatial distribution of jobs and wages leads to geographic variation in these differences.

2.1 Job Choice Set

Given the residential location of a worker, an available job consists of two components: commute time and wage, (τ, w). τ is determined by the relative locations of the worker's home and the job.

To highlight the trade-off between wages and commute time, we assume that each worker faces a log linear relationship between wages and commute time of jobs on the job choice set frontier:

$$\ln(w_{ik}) = \xi_i + \beta_i \ln(\tau_{ik} - \tau^{min}), \ \tau_{ik} \in (\tau^{min}, \tau^{max}], \quad \text{and}$$
$$\beta_i = \bar{\beta}_{jo} + \varepsilon_i,$$

where i is a worker, k is a job on the job choice set frontier faced by the worker, j is the worker's residential location, and o is the worker's occupation. τ^{min} (τ^{max}) is the minimum (maximum) commute time. ξ_i captures individual productivity or ability. This specification allows us to summarize the marginal wage return to commuting with a single parameter β_i. Different workers face different wage returns to commuting, β_i, which is defined as the sum of $\bar{\beta}_{jo}$ and ε_i. $\bar{\beta}_{jo}$ is the marginal wage return to commuting determined by the geography of jobs and ε_i is a random component faced by worker i. More specifically, $\bar{\beta}_{jo}$ is determined by (1) residential location j and (2) the spatial distribution of jobs and their wages in occupation o. If i lives in the suburbs and high-paying jobs in occupation o are concentrated in the central city, then $\bar{\beta}_{jo}$ is large. Conversely, if i lives in the central city, then $\bar{\beta}_{jo}$ can be close to zero or even negative. ε_i captures other components in β_i that cannot be captured by the spatial distribution of jobs. For example, if i's search intensity decreases with commute time or information friction increases with commute time, job openings far away from i may offer lower wages although $\bar{\beta}_{jo}$ can be high.

2.2 Worker

Each worker i has an additive utility function:

$$U(\tau_i, w_i) = \ln(w_i) - \lambda \tau_i.$$

Worker value higher wages but dislike longer commutes, with increasing marginal disutility of commuting relative to wage. λ measures the degree to which workers dislike commuting relative to lower wages. We allow λ to differ by gender, $\lambda \in \{\lambda_m, \lambda_f\}$. Let $U^R \in \mathbb{R}$ be the reservation utility: A worker chooses to work if and only if the corresponding level of utility is greater than U^R.

2.3 Equilibrium Job Choice

Each worker i chooses a job to maximize utility subject to the constraint of job availability:

$$\begin{aligned} &\max_{\tau_i, w_i} \quad U(\tau_i, w_i) \\ &\text{s.t. } \ln(w_i) = \xi_i + \beta_i(\tau_i - \tau^{min}), \ \tau_i \in (\tau^{min}, \tau^{max}]. \end{aligned}$$

The first-order condition yields:

$$\tau_i^* = \begin{cases} \tau^{max}, & \text{if } \beta_i > 0 \text{ and } \frac{\beta_i}{\lambda} > \tau^{max} - \tau^{min} \\ \frac{\beta_i}{\lambda} + \tau^{min}, & \text{if } \beta_i > 0 \text{ and } \frac{\beta_i}{\lambda} \leq \tau^{max} - \tau^{min} \\ \tau^{min}, & \text{if } \beta_i \leq 0. \end{cases}$$

When $\beta_i > 0$ (i.e., there is a trade-off between wages and commutes), workers commute less if they dislike commuting more and they commute more if the wage return to commuting is higher.

To understand how gender differences in λ contribute to the gender commuting and wage gaps, we first consider what happens to the optimal commute time when a worker's disutility of commuting increases. We focus on the case when $\beta_i > 0$ and $\beta_i/\lambda \leq \tau^{max} - \tau^{min}$:

$$\frac{\partial \ln(\tau_i^*)}{\partial \lambda} = -\frac{\beta_i}{\lambda(\beta_i + \lambda \tau^{min})} < 0.$$

If women have higher disutility of commute time than men, the optimal commute time for women is shorter than that of men. Similarly, the effect of λ on the equilibrium wage is

$$\frac{\partial \ln(w_i^*)}{\partial \lambda} = -\frac{\beta_i}{\lambda} < 0.$$

In addition, the magnitude of the effects depends on the wage return to commuting (β_i):

$$\frac{\partial^2 \ln(\tau_i^*)}{\partial \lambda \partial \beta_i} = -\frac{\tau^{min}}{(\beta_i + \lambda \tau^{min})^2} < 0;$$
$$\frac{\partial^2 \ln(w_i^*)}{\partial \lambda \partial \beta_i} = -\frac{1}{\lambda} < 0.$$

The impact of β_i on $\ln(\tau_i^*)$ is larger if λ is smaller. Intuitively, if the utility cost of long commutes is relative mild, then workers will commute longer to reap the wage benefit should β_i be large. However, if the utility cost of long commutes is high, workers have to weigh the benefit of long commutes against the utility cost. Therefore, a higher λ leads τ_i^* to be less responsive to β_i.[3]

The gender gaps in commute time and wages due to preference differentials can also be expressed with a first-order approximation:

$$\ln(\tau_f^*) - \ln(\tau_m^*) = -\frac{\bar{\beta}(\lambda_f - \lambda_m)}{\lambda_m \left(\bar{\beta} + \lambda_m \tau^{min}\right)}, \tag{1}$$
$$\ln(w_f^*) - \ln(w_m^*) = -\frac{\bar{\beta}(\lambda_f - \lambda_m)}{\lambda_m}, \tag{2}$$

where $\bar{\beta}$ is the average wage return to commuting faced by workers. Crucially, a higher $\bar{\beta}$ increases gender gaps in commutes and wages. This is because if $\lambda_f > \lambda_m$, men's commute time is more responsive to $\bar{\beta}$, and therefore the gender commuting gap is larger in locations where workers face larger $\bar{\beta}$.

[3] Alternatively, we can consider what happens to the optimal commute time when the wage return to commute time increases, holding λ constant:

$$\frac{\partial \ln(\tau_i^*)}{\partial \beta_i} = \frac{1}{\beta_i + \lambda \tau^{min}} > 0 \quad \text{if} \quad \beta_i > 0.$$

The optimal commute time is longer if the wage return to commuting is higher. However, larger λ dampens the effect of β_i on commute time.

2.4 Graphical Analysis

We present graphical illustration to further demonstrate the intuition. In Figure 1, upward sloping curves represent indifference curves for a representative man and woman, respectively. The indifference curves are upward sloping because workers prefer higher wages and shorter commutes. Assume that $\lambda_f > \lambda_m$. Then, the female indifference curves are steeper than the male indifference curves. Moreover, since we assume that men and women differ only in the disutility of commuting, they face the same job choice set if they live in the same residential location. The concave curve represents the job choice set frontier faced by the workers, given the residential location. The curvature of the curve captures the wage return to commuting. The set of points below the job choice set frontier represents jobs available to the workers. The optimal job choices are given by the tangential points between the indifference curves and the frontier. This figure illustrates how gender differences in commuting preferences can lead to a gender gap in commutes and wages for otherwise identical workers.

The wage return to commuting Figure 2 illustrates how the curvature of the job choice set frontier (i.e., the wage return to commuting) affects the gender gap in commute time and wages, given the preferences. The figure shows that when the wage return to commuting is low, holding gender-specific utility functions unchanged, the gender commuting gap becomes smaller, which leads to a smaller gender wage gap.

Figure 3 shows the case where workers face a negative return to commuting. In other words, they do not face a trade-off between higher wages and shorter commutes (e.g., financial workers living in downtown Manhattan). Then, they face the same optimal job choice, which is given by the corner solution. In this case, the model predicts no gender commuting and wage gaps.

2.5 Model Implications

The model suggests that the equilibrium gender commuting and wage gaps are jointly determined by gender-specific commuting preferences (λ_m and λ_f) and the wage returns to commuting (β_i) faced by each worker. The sign and magnitude of β_i depend on both where workers live and the spatial distribution of jobs and wages. In particular, the spatial distribution of jabs and wages also varies across occupations.

To build intuition, first, we consider a male financial manager m and a female financial manager f

living in a suburban neighborhood in New York metropolitan area. Assume that f dislikes commuting more than m ($\lambda_f > \lambda_m$), but they are otherwise similar. Since high-paying financial manager jobs in New York metropolitan area are mainly concentrated in Manhattan, these workers face a large β. Then the model predicts relatively large gender commuting and wage gaps. Second, suppose that m and f live in Manhattan and other assumptions remain the same. Now, β should be small or even negative for them. Therefore, the model predicts small or zero gender gaps.

Alternatively, consider a male and a female dentist. Since high paying jobs for dentists are relatively evenly distributed across locations, the wage return to commuting is likely to be small, regardless of their residential locations. Thus, the gender gaps in commute time and wage should not vary across locations.

In summary, the model implies that:

1. For occupations in which high-paying jobs are highly concentrated in some locations, there should be relatively large variation in the gender commuting and wage gaps across locations.

2. For occupations in which high wage-offering jobs are evenly distributed across locations, the gender commuting and wage gaps should be relatively small and vary little across locations.

3 Data and Descriptive Facts

3.1 Data

We use data from two sources. First, we use the American Community Survey (ACS) 2013-2017 5-year sample from the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2019). The data provide individual- and household-level information on various demographic and socioeconomic characteristics, such as gender, race, marital status, education attainment, employment status, working hours, occupation, and income. Moreover, ACS provides workers' self-reported commute time. Lastly, ACS provides residential location at the level of Public Use Microdata Area (PUMA) and working location at the level of Place-of-Work PUMA (PWPUMA).[4] ACS is the main data source for the empirical analysis.

Second, we use the Zip Code Business Patterns (ZCBP) provided by the U.S. Census Bureau. It provides the count of business establishments and employment sizes for each NAICS industry code

[4]PWPUMA roughly coincides with county.

at the zip-code level. We create a crosswalk between industry and occupation using ACS and impute the count of jobs by occupation using the crosswalk.[5]

To measure the spatial distribution of jobs and their wages, we combine wage data from ACS with job counts from ZCBP. First, we use ACS to estimate the means and standard deviations of residual log wages in each occupation and PWPUMA.[6] Second, we combining wage distributions at the PWPUMA level from ACS and the number of jobs at the zip-code level from ZCBP. Lastly, we use Google API to compute commute time between every residential PUMA location and every job at the zip-code level within the same MSA, assuming that workers only consider jobs within the same MSA. Thus, for workers in each residential PUMA j and occupation o, we construct a spatial profile of job commute-wage bundles $\left\{\tau_{jok}, \ln(w_k)\right\}$, where k is job in occupation o and the MSA of j, using data on wages, job locations, and job counts. We use the profile to measure the wage return to commuting $\bar{\beta}_{jo}$. The estimation strategy is described in Section 4.2.

Table 1 provides summary statistics from ACS. We restrict our sample to full-time (35+ hours) workers, aged between 25 and 69. Women in the sample are less likely to be married with spouse present and less likely to have a young child than male workers. Moreover, women are better educated than men. The average *one-way* commute time is 26 minutes for men and 23 minutes for women. The average hourly wage is $30 for men and $24 for women. The gender differences in the average commute time and the average hourly wage are statistically significant. Table A1 in the Appendix provides summary statistics for workers living in four major metropolitan areas focused in this paper. The patterns found in the nationwide sample remain in the sample for each metropolitan area.

3.2 The Geography of Gender Commuting and Wage Gaps

We lay out several empirical facts that motivate the research question. Figures 4 and 5 present gender differences in log commute time and log hourly wage within four major MSAs.[7] We find that there is substantial variation in the gender commuting and wage gaps across locations within MSAs. Moreover, the gender gaps are typically smaller for workers living in the central city compared to

[5]More details the construction of the crosswalk and the imputation are included in Appendix ().

[6]Residual log wages are obtained by controlling for age, race, Hispanic origin, marital status, and education dummies.

[7]We focus on Chicago, San Francisco, Boston, and New York metropolitan areas because there are relatively a large number of PUMAs within these metropolitan areas.

those living in the suburbs.[8]

Figure 6 presents binned scatter plots of gender differences in log commute residuals and log hourly wage residuals by residential PUMA based on the nationwide sample. PUMAs are divided into 20 equal bins based on the distance to downtown.[9] We find that 10 miles away from downtown is associated with a 1.9% (1.1%) increase in the gender commuting (wage) gap.

Figure 7 presents binned scatter plots of gender differences in log commute residuals and log hourly wage residuals by residential PUMA for financial workers and dentists separately. This is because high-paying jobs for financial workers are likely to concentrated in the central city, while high-paying jobs for dentists are relatively less geographically concentrated. We find that for financial workers, 10 miles away from downtown is associated with a 3.9% (1.5%) increase in the gender commuting (wage) gap. For dentists, 10 miles away from downtown is associated with a 5.4% decrease in the gender commuting gap. We do not find a notable correlation between the gender wage gap and distance to down for dentists.

4 Empirical Strategy

Based on the job choice model, we analyze how much gender differences in commuting preferences and spatially different wage returns to commuting contribute to the geographic patterns of the observed gender commuting and wage gaps. To evaluate the model quantitatively, we need to estimate two sets of parameters: (1) gender-specific preferences for commuting λ and (2) the wage return of commuting β faced by each worker. Graphically, λ represents the slope of an indifference curve and β represents the slope of the job choice set frontier. We describe estimation procedures for λ and β, separately.

4.1 Estimation of Commuting Preference λ

We first estimate gender-specific preferences for commuting. The goal is to trace out workers' trade-off between commute time and wage on the same utility level, or to estimate the slope of their indifference curves: $U = \ln(w_i) - \lambda_s \tau_i,\ s \in \{\text{male } (m),\ \text{female } (f)\}$. If workers are identical and can

[8] The patterns remain if we use residual commute time and residual wages, controlling for age, race, Hispanic origin, marital status, whether having at least a child under age 18, education, and occupation dummies.

[9] Log commute residuals and log hourly wage residuals are obtained by controlling for gender-specific dummies for age, marital status, whether having a child younger than age 18, race, Hispanic origin, education, occupation, year, and MSA.

freely move across locations, the level of utility should be equalized across locations for every worker with optimal choices. Under this assumption, the observed job bundles $(\ln(w), \tau)$ should line up on the same indifference curve. Therefore, simply regressing log wages on commute time should yield an unbiased estimate of λ_s.

However, the assumption of equalized utility is highly simplified and unlikely to hold in the data. If workers are heterogeneous or if job opportunities available for identical workers differ for idiosyncratic reasons, a simple regression would yield biased estimates. Below we discuss two reasons that are likely to cause biased estimates from simple regressions.

Location sorting by ability If workers are heterogeneous in ability, the level of utility may differ across workers. In other words, the observed bundles of wages and commute time may locate on different indifference curves. If workers with different levels of ability sort into neighborhoods with different distances to high-paying jobs, a simple regression would yield a biased estimate of the slope of indifference curves. For example, if workers with higher ability choose to live in the suburbs far away from high-paying jobs for some unobserved reasons, a simple regression could overestimate λ_s.[10] Alternatively, if high-ability workers sort into neighborhoods close to job centers, a regression estimator may suffer from downward bias. Figure 8 provides a graphical illustration of the first case.

Random job arrival The second reason that regression estimation could yield biased estimates is that observed job bundles of wages and commute time may belong to different indifference curves due to the randomness of job arrivals. To illustrate, consider two workers with identical abilities and live in same location. Worker i chooses the best available job A on the job choice set frontier. Although two workers have same ability level, i' receives an additional job B idiosyncratically, which pays as much as A does, but is closer to their residential location. In this scenario, worker i' has a higher utility level than worker i, and thus these two observations belong to two different indifference curves. Tracing together these two bundles will yield an underestimation of the slope of their indifference curves. Therefore, even after controlling for workers earning ability and location sorting, two observationally equivalent workers may still be on different indifference curves due to randomness of job arrivals. Figure 9 provides a graphical illustration of the example.

[10] High ability workers may sort into suburban neighborhoods with high amenities (school, law enforcement, larger houses, etc.) Or high ability workers may have weaker distaste to commuting.

To overcome the challenges due to location sorting by ability and the randomness of wage realization, we construct a lower-envelope estimator to identify the slope of the indifference curve corresponding to workers reservation utility (*reservation curve* from here on). We first residualize log hourly wage and commute time by with various demographic and location fixed effects to account for potential sorting by ability. We then estimate the slope of indifferent curves exploiting the theoretical prediction that the observed job choice bundles should locate on or above the reservation curve. Since reservation curve is the lower envelope of the chosen job bundles, the slope of workers' indifference curves should coincide with the slope of the lower envelope of observed job bundles.

For the moment, we assume that holding demographic and location controls constant, workers have the same reservation utility U^R. We then estimate the lower envelope of observed job bundles using a nonparametric frontier estimator proposed by Cazals et al. (2002), which is robust to extreme values or outliers.

The set of *all possible* observed job bundles chosen by workers is given by

$$\Psi = \{(\tau, w) \in \mathbb{R}^2 |\ U(\tau, w) \geq U^R\}.$$

Since workers prefer higher wages and shorter commutes, if $(\tau, w) \in \Psi$, then $w' \geq w$ and $\tau' \leq \tau$ implies that $(\tau', w') \in \Psi$. We furthermore assume that

Assumption 1 *If $(\tilde{\tau}, \tilde{w})$ is in the interior of Ψ, then $P(w < \tilde{w}|\ \tau = \tilde{\tau}) > 0$.*

In other words, we assume that workers who are on the indifference curve corresponding to the reservation utility are represented in the data.

The lower boundary of all observed job bundles is given by the function:

$$\phi(\tau) = \inf\{w|(\tau, w) \in \Psi\}.$$

Cazals et al. (2002) propose a nonparametric method that is more robust to extreme values or noise. Let $(w^1, ..., w^m)$ be m independent identically distributed random variables generated by the wage distribution given $\tau \geq \tilde{\tau}$. Define the expected minimum wage function of order m denoted by $\psi_m(\tilde{\tau})$ as

$$\phi_m(\tilde{\tau}) = E[\min(w^1, ..., w^m)|\ \tau \geq \tilde{\tau}], \tag{3}$$

assuming the expectation exists. Intuitively, $\psi_m(\tilde{\tau})$ is the expected lowest wage level that would be observed among workers whose commute time is at least $\tilde{\tau}$, out of m draws. Cazals et al. (2002) shows that for any fixed value $\tilde{\tau}$, $\lim_{m\to\infty}\phi_m(\tilde{\tau}) = \phi(\tilde{\tau})$. To estimate $\phi_m(\tilde{\tau})$, consider an i.i.d. sample (τ_i, w_i), $i = 1, ..., n$ of the random vector (τ_i, w_i). The estimator of the expected minimum wage function of order m is defined by

$$\hat{\phi}_{m,n}(\tilde{\tau}) = \hat{E}[\min(w^1, ..., w^m)|\ \tau \geq \tilde{\tau}], \tag{4}$$

which can be easily computed in practice. More specifically, let $n(\tilde{\tau})$ be the number of observations of τ_i greater or equal to $\tilde{\tau}$. For $j = 1, ..., n(\tilde{\tau})$, let $w^{\tilde{\tau}}_{(j)}$ be the jth order statistic of the observations w_i such that $\tau_i \geq \tilde{\tau} : w^{\tilde{\tau}}_{(1)} < w^{\tilde{\tau}}_{(2)} < ... < w^{\tilde{\tau}}_{n(\tilde{\tau})}$. Then,

$$\hat{\phi}_{m,n}(\tilde{\tau}) = w^{\tilde{\tau}}_{(1)} + \sum_{j=1}^{n(\tilde{\tau})-1} \left[\frac{n(\tilde{\tau}) - j}{n(\tilde{\tau})}\right]^m (w^{\tilde{\tau}}_{(j+1)} - w^{\tilde{\tau}}_{(j)}). \tag{5}$$

Cazals et al. (2002) establish the asymptotic properties of the estimator. In particular, they show that as m and n grow larger, $\hat{\phi}_{m,n}(\tilde{\tau})$ approaches $\phi(\tilde{\tau})$. Choosing a finite m makes the estimator more robust to outliers that may in fact fall below the reserve curve due to measurement error. Therefore, $\hat{\phi}_{m,n}(\tilde{\tau})$ is a robust and consistent estimator of the minimum wage that a worker is willing to accept in order to work with commute time $\tilde{\tau}$.

A sufficient assumption for the identification of λ is that holding demographic and location controls constant, workers have the same level of reservation utility. The identification strategy still works if workers of unobservable higher ability have higher levels of reservation utility, as long as there is no location sorting. A threat to identification is that workers with higher unobservable ability have higher levels of reservation utility, *and* these workers also tend to live in suburban neighborhoods (and therefore tend to commute more). We alleviate the problem by controlling for residential location fixed effects, and their interactions with occupation indicators and education indicator.

4.2 Measurement of the Wage Return to Commuting β

We construct a measurement of the wage return to commuting $\bar{\beta}_{jo}$ that is determined by residential locations j and occupations o. Note that $\bar{\beta}_{jo}$ does not include any random components faced by individual workers. In the model, we use $\bar{\beta}_{jo}$ to represent the slope of the job choice set frontier. Therefore, we measure $\bar{\beta}_{jo}$ by estimating the slope of the upper envelope of available job bundles faced by workers in residential location j and occupation o, using detailed data on job locations and wages by occupation. Intuitively, for each given commute time, each worker considers the job that offers the highest wage, because otherwise she cannot be maximizing her utility. Therefore, the slope of the maximum log wage over commuting captures the marginal wage return to commuting.

Suppose workers choose a job from all job openings in her occupation and the MSA that contains her residential PUMA. Let $\Psi_{jo} = \left\{(\tau_{jok}, \ln(w_k))\right\}$ be the set of available jobs faced by workers in residential PUMA j and occupation o. We take the following two steps to trace out the slope of the upper envelope of Ψ_{jo}. First, we take each job $(\tau_{jok}, \ln(w_k)) \in \Psi_{jo}$, and rank $\ln(w_k)$ among other jobs with similar commute time $\Psi_{jok} \equiv \{(\tau_{jok'}, \ln(w_{k'})) \in \Psi_{jo} | \; \tau_{jok} - \epsilon \leq \tau_{jok'} \leq \tau_{jok} + \epsilon\}$, where ϵ is a bandwidth. We set ϵ to be a fixed fraction of the 10-90 gap of the log commute time of all available jobs in Ψ_{jo}. If k offers the highest wage among all jobs in Ψ_{jok}, we retain it as part of the upper envelope. We then repeat the procedure for every job in Ψ_{jo}. The procedure produces a subset of job openings that approximates the upper envelope. Formally, the estimated upper envelope is

$$\Psi^*_{jo} = \left\{(\tau_{jok}, \ln(w_k)) \middle| \; \ln(w_k) = \max_{(\tau_{jk'}, \ln(w_{k'})) \in \Psi_{jok}} \ln(w_{k'})\right\}$$

Next, we regress log wage on commute time using jobs in Ψ^*_{jo} to obtain the slope of the upper envelope, namely the wage return to commuting for workers in location j and occupation o.[11]

However, in reality, jobs arrive randomly and workers have limited attention, so it is not reasonable to use all available jobs in the MSA of PUMA j and occupation o observed in the data to estimate $\bar{\beta}_{jo}$. Therefore, to estimate $\bar{\beta}_{jo}$, we simulate 50 commute-wage bundles by randomly drawing jobs from the spatial distribution of jobs and wages in occupation o and the MSA of PUMA j, and we conduct this simulation N times independently. In each round n, we apply the upper envelope estimator to the 50 simulated jobs and obtain an estimate $\widehat{\beta^n_{jo}}$. The estimated wage return to commuting is $\widehat{\beta_{jo}} = \frac{1}{N}\sum_{n=1}^{N} \widehat{\beta^n_{jo}}$.

[11]The estimated slope can be sensitive to the choice of the bandwidth ϵ. If ϵ is large, bundles in Ψ_{jo} are likely to be sparse. If ϵ is small, there are more bundles in Ψ_{jo}, but they can be less smooth. We set ϵ to be 10% of the 10-90 gap of the log commute time. For robustness, we also use alternative ϵ.

5 Results

5.1 Reduced Form Evidence

In this section, we provide reduced-form evidence on gender differences for commuting. Table 2 presents the OLS estimates of the following equation:

$$\begin{aligned}\ln(w_{ijt}) =& \alpha + \theta Fem_{ijt} + \gamma\tau_{ijt} + \delta Fem_{ijt} \cdot \tau_{ijt} \\ &+ X_{ijt}\pi_s + d_{st} + d_{sj} + d_{so} + d_{sjo} + \epsilon_{ijt},\end{aligned}$$

where i denotes individual, j denotes residential PUMA, t denotes year, s denotes sex, and o denotes occupation. $\ln(w_{ijt})$ is log wage per hour, Fem_{ijt} is an indicator for being female, τ_{ijt} is one-way commute time in hour, and X_{ijt} is a vector of individual characteristics.

Table 2 Column 1 shows the estimates without any controls. The results suggest that a one-hour longer one-way commute is associated with 11% higher wages for women compared with men. In Column 2, we control for individual characteristics, including sex-specific dummy variables for age, race, Hispanic origin, marital status, whether having a child younger than age 18, and education. We also include sex-specific year fixed effects, occupation fixed effects, and residential PUMA fixed effects. In Column 3, we furthermore control for a sex-specific interaction of occupation and residential PUMA. In particular, controlling for the residential location and its interaction with occupation can address potential sorting problems. For instance, more ambitious workers (in some occupations) may choose to live in the central city in order to stay closer to high-paying jobs and they also tend to earn more. The estimate in Column 3 suggests that a one-hour longer one-way commute is associated with 4.7% higher wages for women compared with men.

Although we can address the potential sorting problems, we may not interpret the OLS estimate of δ as the average gender difference in commuting preferences. This is because there can be other unobserved attributes such as worker ability that may confound wage effect of commuting. If so, by estimating the above equation, we may mistakenly fit workers along different indifference curves with a single estimated line. To provide evidence on whether ability bias is likely to be large, we *exclude* education dummies in Column 4. We do not find a very large change in the estimate of δ. Even without unobserved attributes, the randomness of job offers may still locate similar workers along different indifference curves.

Table 3 shows the estimates for workers who are single and married, respectively. Panel A presents the results for single workers (or married workers whose spouses are absent). The estimates suggest that a one-hour longer one-way commute is associated with 0.2-1.5% *lower* wages for single women compared with single men, depending on their residential areas. Nevertheless, all the estimates are not statistically significant. Panel B presents the results for married workers whose spouses are present. The estimates of δ range from 5.3-10.7%, which are around twice as large as the estimates for all workers. A potential problem associated with the estimates in Panel B is marital sorting and couples' co-location problem. For instance, a couple may choose to live closer to the secondary earner so that he or she could easily take care of the family. This may confound the wage effect of commuting. To deal with the concern, we control for spouse's commute time and log working hours in Panel C. The estimates of δ in Panel C are very comparable with those in Panel B.

5.2 Commuting Preferences

[Estimates of λ are preliminary and subject to changes.]

Table 4 shows the estimates of λ_s using the lower envelope estimator. Table 4 Column 1 shows that the estimated λ_s is 0.2998 for men and 0.3943 for women. This means that in order to increase one-way commute time by one hour and to maintain the same level of utility, a male worker has to be compensated by 29.98% higher wages, whereas a female worker needs to be compensated by 39.43% higher wages. On average, women's disutility of commuting is roughly 25% higher than that of men.

Interestingly, estimates for workers who are single show that male workers and female workers do not differ much in terms of their preferences for commuting. The estimate for λ_{male} is actually slightly higher than the estimate for λ_{female}, though not statistically significant. Contrasting with single workers, the estimates for married workers, female workers exhibit much stronger distaste for commuting than male workers. Note that λ_{male} for married workers is slightly lower than for single workers, but λ_{female} for married workers is higher than that for single workers. The estimates are similar if we restrict the sample to married workers with children.

In addition, we also present estimates by splitting the samples into workers with college degrees and workers without college degrees. The sizes of λ_s are slightly higher for workers without college degrees. However, the gap in preferences by gender is somewhat larger among workers with college degrees. The overall picture of sizable gap in preferences for commuting hold for both education groups.

Furthermore, we also conduct estimation by splitting the sample by MSA. The basic result that preferences for shorter commuting is stronger among female workers than among male workers holds for all MSAs that we examine. Table 5 shows separate estimates of λ_s for four selected MSAs: New York, Chicago, San Francisco and Boston. The gender differences in preferences is confirmed in all four MSAs, though statistical power is weaker within each subsample.

In this draft version, we estimate λ_s by assuming there is no heterogeneity across residential locations. But workers could be sorting across location based on their preferences for commuting. Intuitively, workers who dislike commuting more would prefer to live in the central city neighborhoods where jobs are closer. A result of such spatial sorting is that the average value of λ_s would be larger in central cities. If female workers have higher λ_s in general, sorting effect could be stronger for working females. Estimation of location-specific λ_s is in progress, which we expect to have available in the next draft.

5.3 The Wage Return to Commuting

We estimate $\bar{\beta}_{jo}$ for the New York MSA. This is because the estimation of $\bar{\beta}_{jo}$ requires wage data based on job locations. We use data from ACS, which provides information on wages and job locations at the PWPUMA level. We focus on the New York MSA because PWPUMAs there are typically small, mostly resemble counties. Nevertheless, other MSAs (e.g., Chicago) contain some extremely large PWPUMAs, which prohibit us from generating accurate spatial wage distributions. Within the New York MSA, we estimate $\bar{\beta}_{jo}$ for each residential PUMA j and occupation o.

Figure 10 shows the distribution of $\widehat{\beta_{jo}}$ for workers in the New York MSA. The mean is 0.2813, the median 0.2827, and the standard deviation is 0.1454. This means that for an average worker, the spatial distribution of jobs implies that increasing commute time by 10% is associated with a 2.8% increase in the wage of the best job offer. Notice that $\widehat{\beta_{jo}}$ is positive for most workers. This is not surprising because a longer commute radius is associated with a larger number of job openings, and therefore a higher probability of high wage realization. As a result, even if jobs are uniformly distributed across locations, with identical wage distributions, each worker would face a positive $\bar{\beta}_{jo}$.

To demonstrate the geographic distribution of $\widehat{\beta_{jo}}$, we plot the $\widehat{\beta_{jo}}$ estimates on a map in Figure (). Alluding back to the examples we use in the introduction, we plot $\widehat{\beta_{jo}}$ for financial managers and dentists in Figure (). One notice that despite both jobs are classified as highly skilled, the spatial distribution of commuting friction facing workers in these occupations are dramatically different. For financial managers, $\widehat{\beta_{jo}}$ tend to be small in Manhattan and large in the suburbs, while for dentists $\widehat{\beta_{jo}}$ tend not to be related to the distance to center city. Financial manager jobs are highly concentrated in Manhattan and have large residual variation in pay among those jobs in Manhattan. As a result, job offers with very high wages tend to realize in Manhattan. For financial managers living in Manhattan, they tend to receive high wage jobs nearby, hence the estimates for $\widehat{\beta_{jo}}$ tend to low. In contrast, dental clinics tend to be scattered around the MSA, centered locally around retail clusters. In addition, residual variation in wages does not differ much in center city vs. in suburbs. Hence, $\widehat{\beta_{jo}}$ are uncorrelated with distance to downtown.

5.4 Model Predicted Gaps versus Observed Gaps

To provide evidence on the reliability of the model, we compared the model predicted gaps in commutes and wages with the observed gaps in the model.

We focus on the case when $\beta_i > 0$ and $\frac{\beta_i}{\lambda_s} \leq \tau^{max} - \tau^{min}$. Then the optimal commute time predicted by the model is

$$\tau_i^* = \frac{\bar{\beta}_{jo} + \varepsilon_i}{\lambda_s} + \tau^{min}.$$

Assuming that workers do not face random shocks in the wage return to commuting (i.e., $\varepsilon_i = 0$), we can compute a model predicted commute time for each worker using $\widehat{\beta_{jo}}$ and $\widehat{\lambda_s}$ estimated in the previous sections:

$$\widehat{\tau_i^*} = \frac{\widehat{\beta_{jo}}}{\widehat{\lambda_s}} + \tau^{min}.$$

Figure 11 presents the model predicted gender gap in log commute ($\ln(\widehat{\tau_i^*})$) versus the observed gender gap in log commute ($\ln(\tau_i)$). The result suggests that the gender gap in log commute time predicted by the model using estimated gender-specific commuting preferences and the wage return to commuting implied by occupation-specific spatial distribution of wages is highly correlated with the observed gender commuting gap.

6 Decomposing the Gender Wage Gap

[Results of counterfactual analysis are preliminary and subject to changes.]

In this section, we use the estimated job choice model to unpack how preference differential and spatial friction contributes to the gender wage gap. In the current draft, we quantify (1) how much gender differences in commuting preferences contribute to the gender wage gap, and (2) how much commuting friction contributes to the gender wage gap.

6.1 Gender Differences in Commuting Preferences

To quantify the contribution of commuting preferences to the gender wage gap, we use the estimated model to compute the gender wage gap under the counterfactual scenario that men and women have the same commuting preference (i.e., $\lambda_m = \lambda_f$), holding all else equal.

We focus on the case when $\beta_i > 0$ and $\frac{\beta_i}{\lambda_s} \leq \tau^{max} - \tau^{min}$. Then the optimal commute time predicted by the model is

$$\tau_i^* = \frac{\bar{\beta}_{jo} + \varepsilon_i}{\lambda_s} + \tau^{min}.$$

Substituting the observed commute time τ_i of worker i for τ_i^* and substituting $\widehat{\beta_{jo}}$ and $\widehat{\lambda_s}$ estimated in the previous sections for $\bar{\beta}_{jo}$ and λ_s, we can back out the implied values of ε_i, denoted by $\widehat{\varepsilon_i}$. After obtaining $\widehat{\varepsilon_i}$, we re-commute the model predicted commute time for women, under the counterfactual scenario that their disutility of commuting is $\widehat{\lambda_m}$:

$$\widehat{\tau_i} = \frac{\widehat{\beta_{jo}} + \widehat{\varepsilon_i}}{\widehat{\lambda_m}} + \tau^{min}.$$

The counterfactual wages for women is given by

$$\widehat{\ln(w_i)} = \ln(w_i) + (\widehat{\beta_{jo}} + \widehat{\varepsilon_i})(\ln(\widehat{\tau_i} - \tau^{min}) - \ln(\tau_i - \tau^{min})).$$

Assuming men's wages remain the same, Table 6 shows how much the model explained gender wage gap will decrease if women have the same commuting preference as men do. Column 1 suggests that if women have the same disutility of commuting as men, their average wage would increase by 0.0426 log points. The unconditional gender gap in log wage is 0.1264 log points. Therefore, the model predicts that eliminating gender differences in commuting preferences would reduce the gender wage gap by 33.7%.

6.1.1 Geographic Variation in the Role of Commuting Preference Differentials

Table 6 Columns 2-5 show that the contribution of commuting preferences to the gender wage gap differs across residential locations. In particular, for workers living close to the central city, gender differences in commuting preferences play a more important role, accounting for 36.7% (26.7%) of the gender wage gap among those living 15-30km (more than 30km) away from downtown. However, among workers living within 5km (5-15km) from downtown, gender differences in preferences can only account for 18.2% (11.6%) of the gender wage gap. These results suggest that commuting friction is likely to play an important role in inducing the gender wage gap. Preference differentials alone cannot explain the geographic variation in the gender wage gap.

6.2 Reducing Commuting Friction

We assess how much commuting friction contributes to the observed gender wage gap. To conduct this exercise, we hold workers' preference parameters constant and consider what happens to the optimal job choices if the commute time to all jobs in each worker's job choice set is reduced by 10%, 20%, 50%, and 90%. We recompute the gender wage gap as a result of commute time reductions. Table 7 shows how much the model explained gender wage gap will decrease as a result of reduced commuting friction. The results suggest that reducing commuting friction for all jobs (e.g., through improving transportation or traffic conditions) can moderately reduce the gender wage gap.

In the next step, we attempt to evaluate how much the gender gap can be narrowed by re-organizing spatial job distributions.

7 Conclusion

Under construction...

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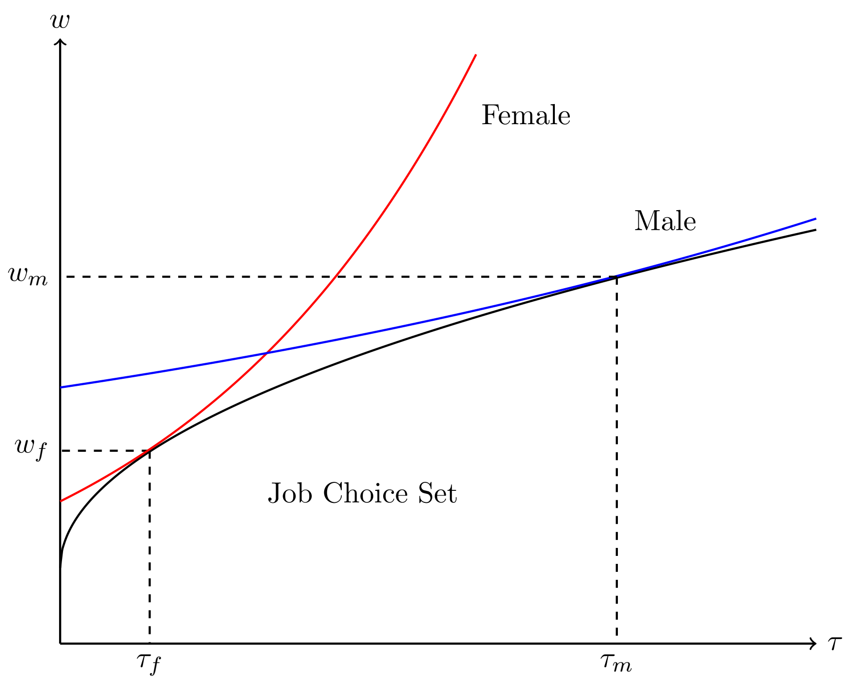


Figure 1: Indifference Curves and Job Choice Set Frontier

Note: The red and blue convex curves represent the indifference curves for a representative female and male worker, respectively. They face the same job choice set, and the concave curve represents the choice set frontier. Tangent points (τ_f, w_f) and (τ_m, w_m) represent the optimal job choice for the female and male worker, respectively.

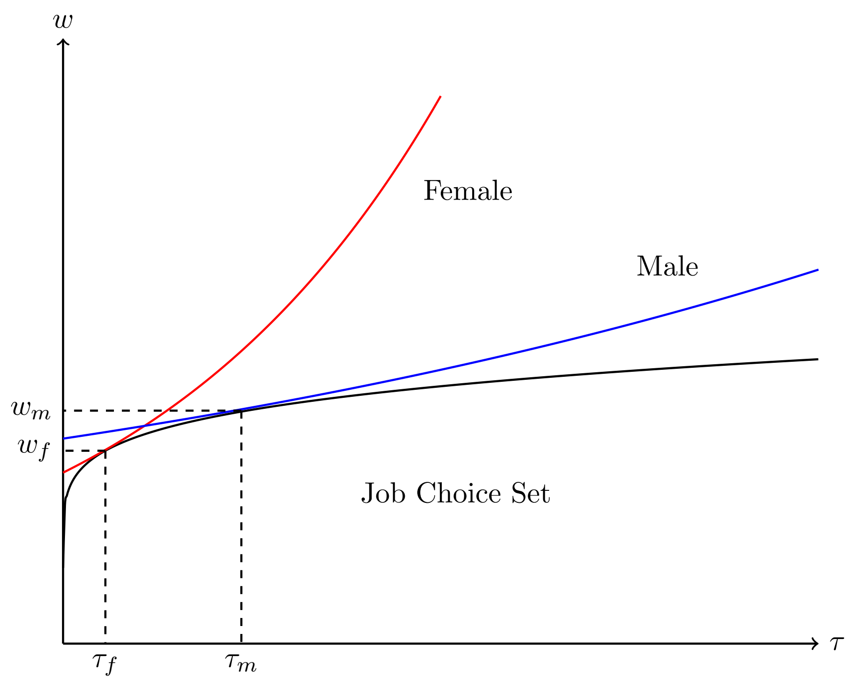


Figure 2: Indifference Curves and Job Choice Set Frontier: Low Wage Return to Commuting

Note: The red and blue convex curves represent the indifference curves for a representative female and male worker, respectively. They face the same job choice set, and the concave curve represents the choice set frontier. Tangent points (τ_f, w_f) and (τ_m, w_m) represent the optimal job choice for the female and male worker, respectively.

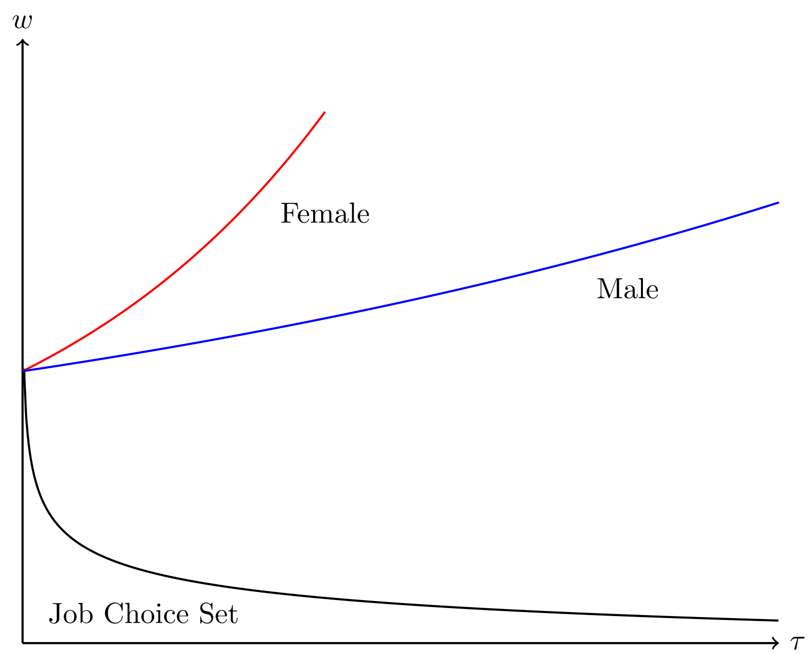
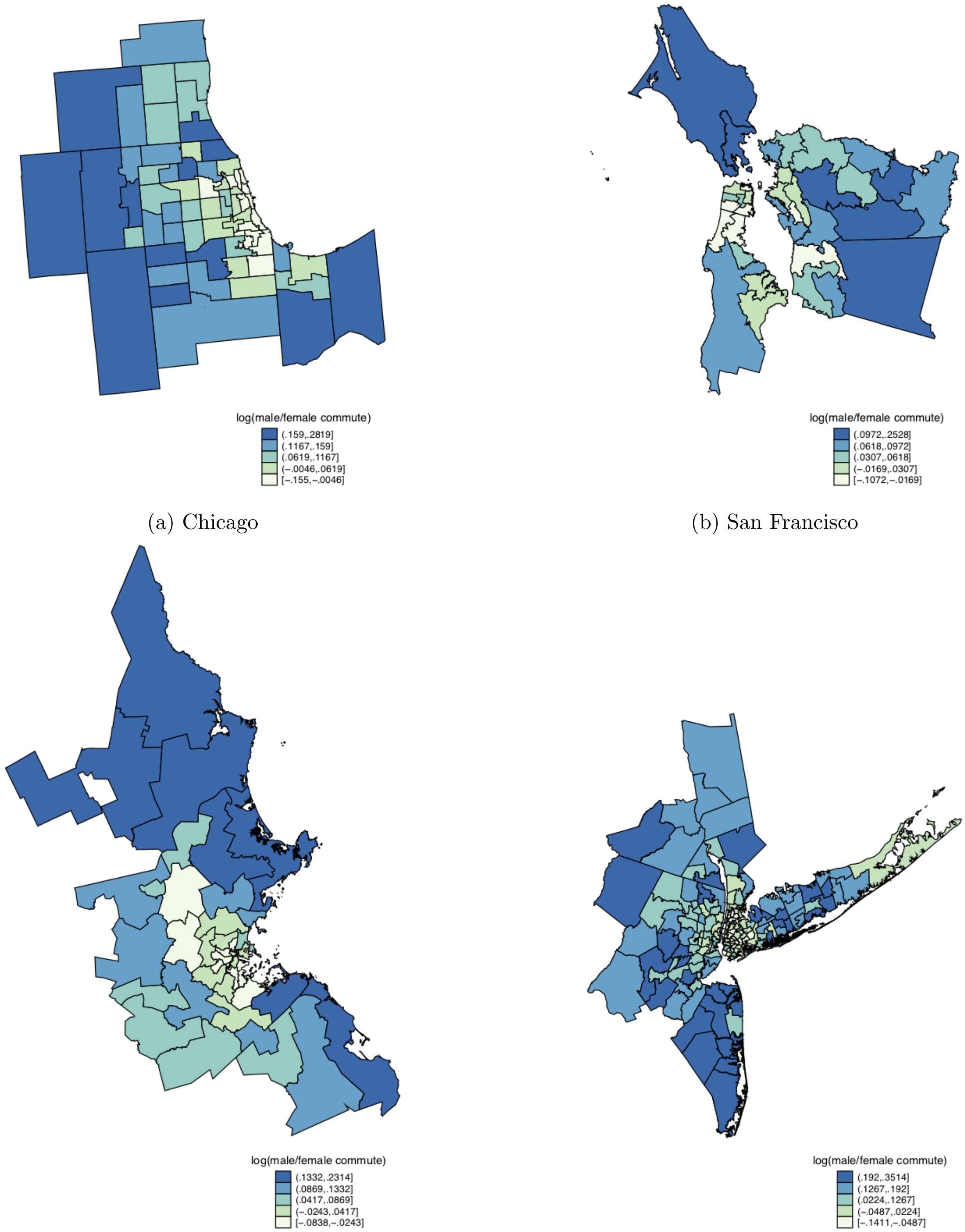


Figure 3: Indifference Curves and Job Choice Set Frontier: Negative Wage Return to Commuting

Note: The red and blue convex curves represent the indifference curves for a representative female and male worker, respectively. They face the same job choice set, and the concave curve represents the choice set frontier. Two workers have the same optimal job choice, which is given by the corner solution.



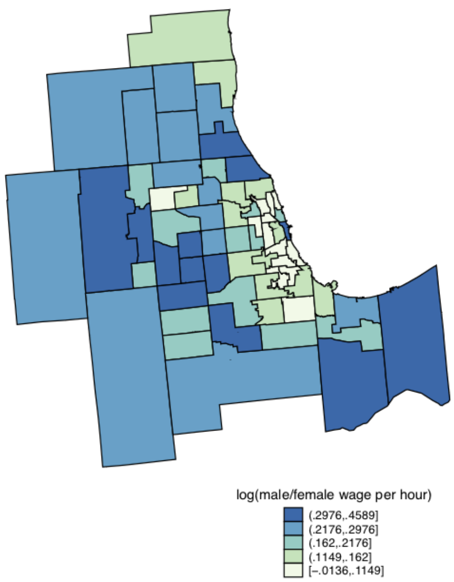
(a) Chicago

(b) San Francisco

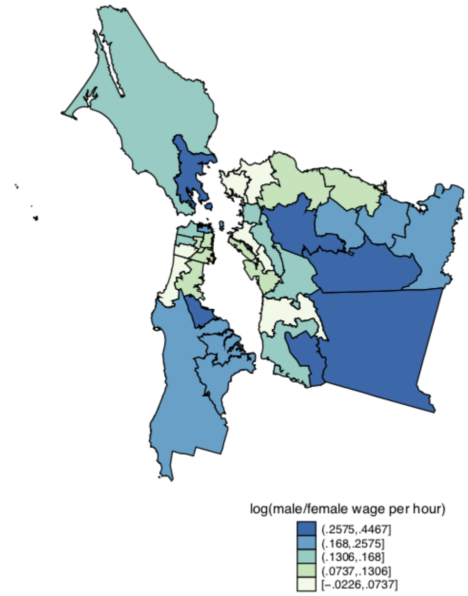
(c) Boston

(d) New York

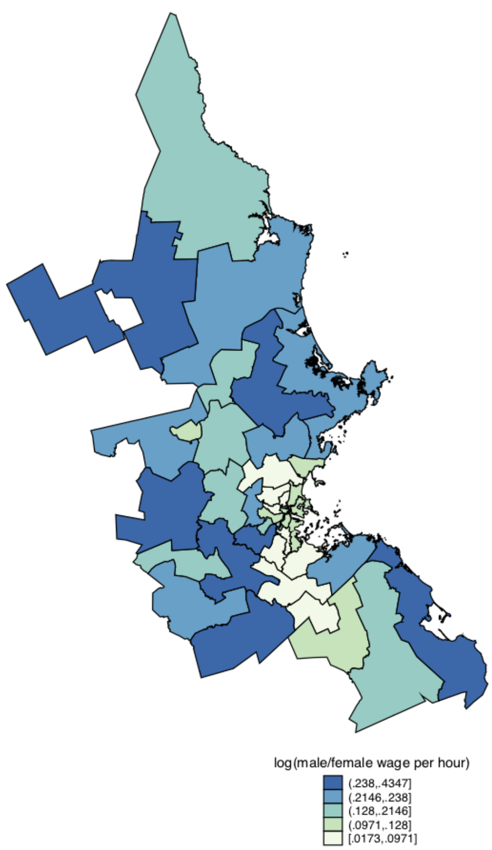
Figure 4: Gender Differences in Commute Time within Four Metropolitan Areas



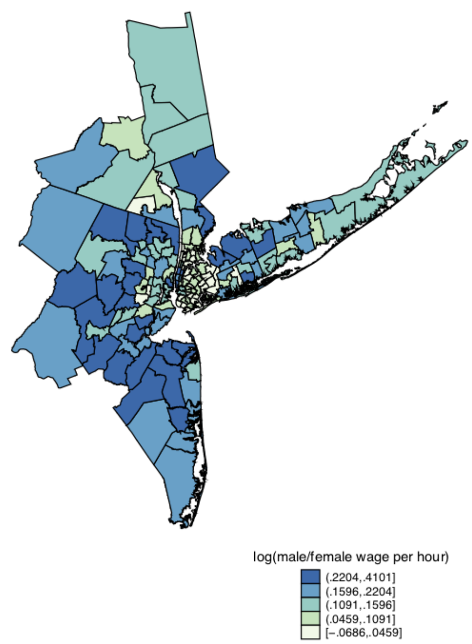
(a) Chicago



(b) San Francisco

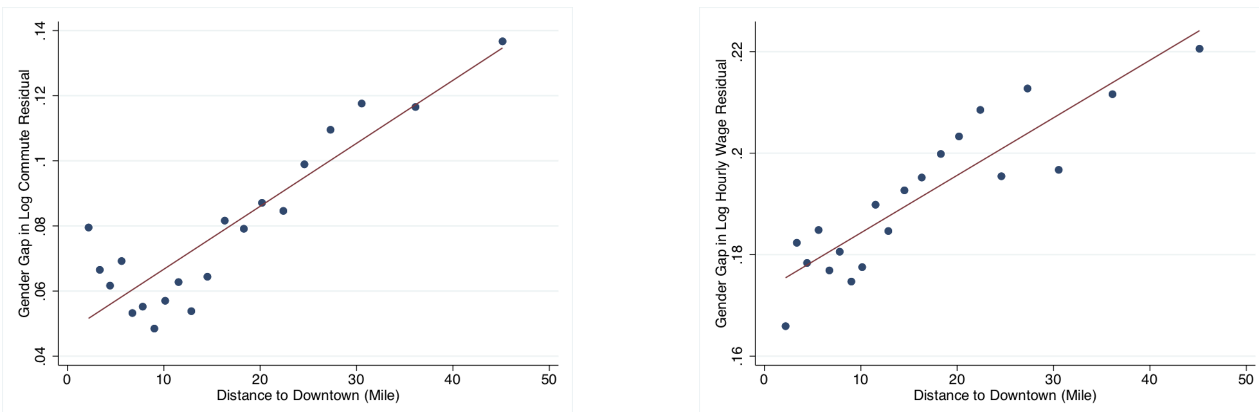


(c) Boston



(d) New York

Figure 5: Gender Differences in Log Hourly Wage within Four Metropolitan Areas

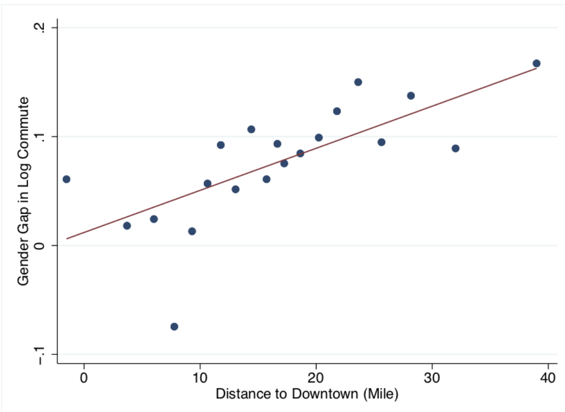


(a) Gender Commuting Gap

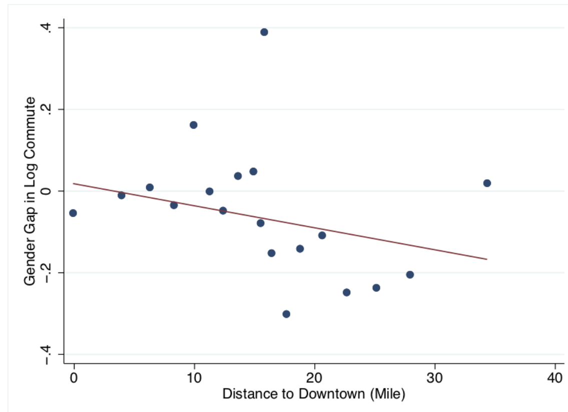
(b) Gender Wage Gap

Figure 6: Gender Gaps and Distance to Downtown

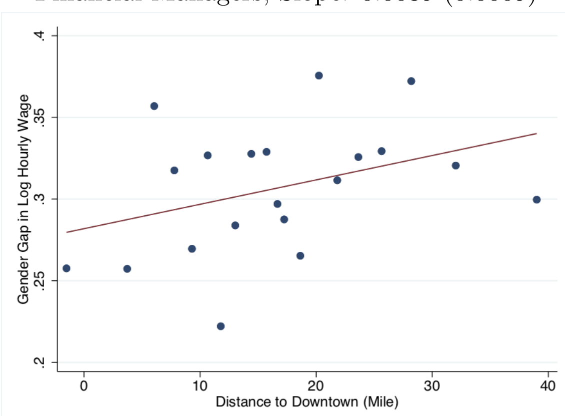
Note: The figures present binned scatter plots of gender differences in log commute residual and log hourly wage residual, by residential PUMA. The variables are residualized on dummies for age, marital status, whether having a child younger than age 18, race, Hispanic origin, education, occupation, year, and MSA. To construct the figures, we bin PUMAs into 20 equal groups based on the distance to downtown. The slope of the fitted line is 0.0019 (0.0001) in Panel (a), and 0.0011 (0.0001) in Panel (b).



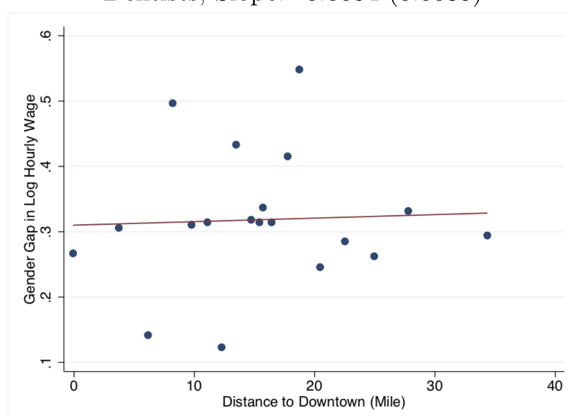
(a) Gender Commuting Gap
Financial Managers, Slope: 0.0039 (0.0009)



(b) Gender Commuting Gap
Dentists, Slope: -0.0054 (0.0035)



(c) Gender Wage Gap
Financial Managers, Slope: 0.0015 (0.0008)



(d) Gender Wage Gap
Dentists, Slope: 0.0005 (0.0037)

Figure 7: Gender Gaps and Distance to Downtown: By Occupation

Note: The figures present binned scatter plots of gender differences in log commute residual and log hourly wage residual, by residential PUMA, for financial managers and dentists, respectively. The variables are residualized on MSA dummies. To construct the figures, we bin PUMAs into 20 equal groups based on the distance to downtown.

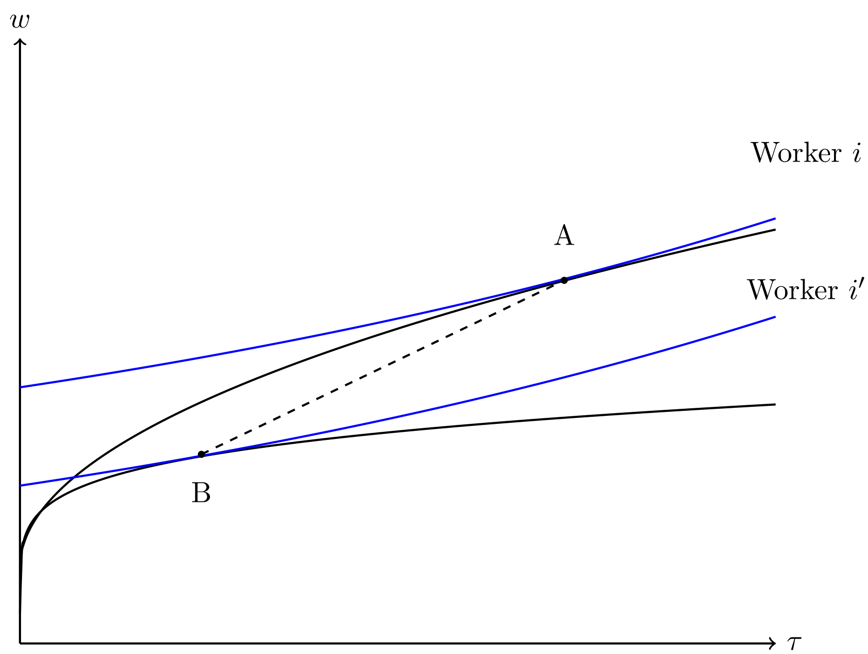


Figure 8: Location sorting by ability

Notes: The figure illustrates why a simple regression may lead to a biased estimate of the slope of difference curves due to location sorting by ability. Assume worker i has higher ability than worker i', and worker i prefers living in the suburbs while worker i' prefers living in the center city. Worker i faces a higher job choice set frontier than i'. Worker i chooses point A while worker i' chooses point B. Tracing out points A and B would lead to an upward biased estimate of the slope of indifference curves.

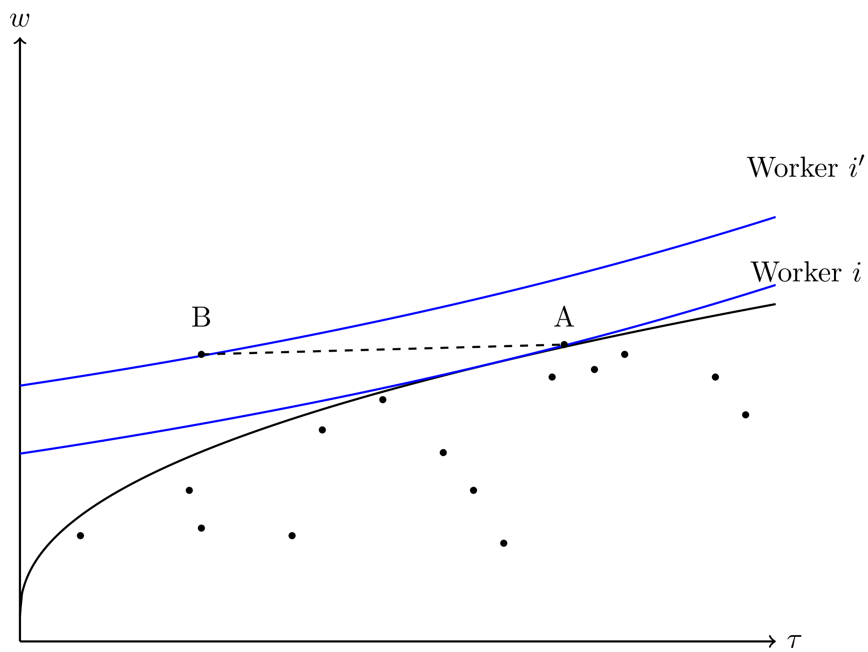


Figure 9: Random job arrival

Notes: The figure illustrates why a simple regression may lead to a biased estimate of the slope of difference curves due to the randomness of job arrival. If job openings are idiosyncratic across workers, then two identical workers may receive slightly different sets of jobs. Assume worker i only receive jobs within her job choice set and chooses point A along the frontier. Worker i' receives an additional job offer B idiosyncratically, which is closer and pays similar wage as A. Therefore, worker i' would accept B. In this case, tracing out points A and B would underestimate the slope of indifference curves.

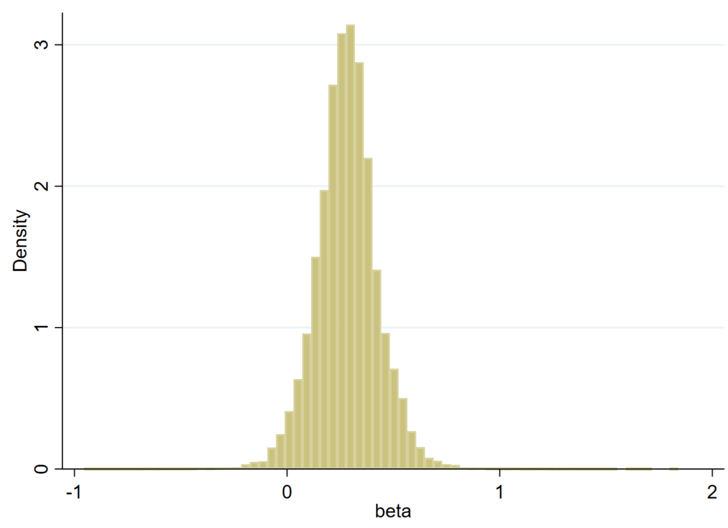


Figure 10: Distribution of estimated $\widehat{\beta_{jo}}$

Note: This figure shows the histogram of estimated $\widehat{\beta_{jo}}$. Each observation of the data is a worker observed in the ACS micro-data. For each worker, we assign the estimated $\widehat{\beta_{jo}}$ based on his/her PUMA location of residence and occupation. The sample are weighted by personal sampling weight (perwt)

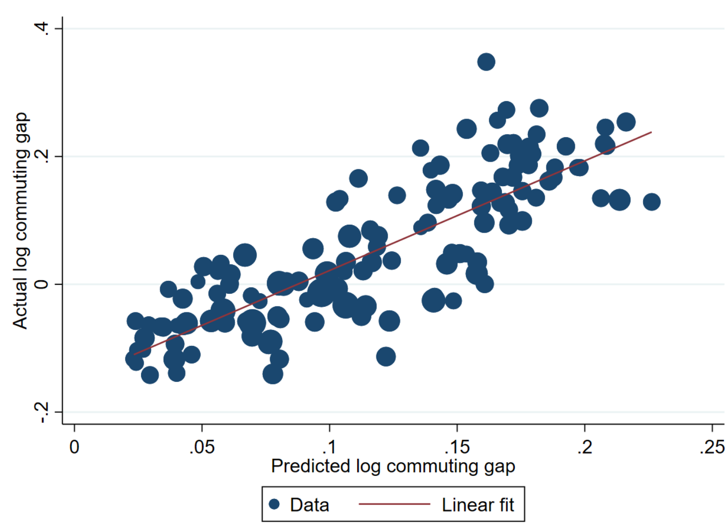


Figure 11: Model Predicted Gap in Log Commute vs. Observed Gap

Note: The figure plots the observed gender gap in log commuting time against model-predicted gender gap in log commuting time that is attributed to differential preferences at PUMA level. Each dot represents a unique PUMA location in the New York MSA. The size of each dot represents the number of workers in each PUMA.

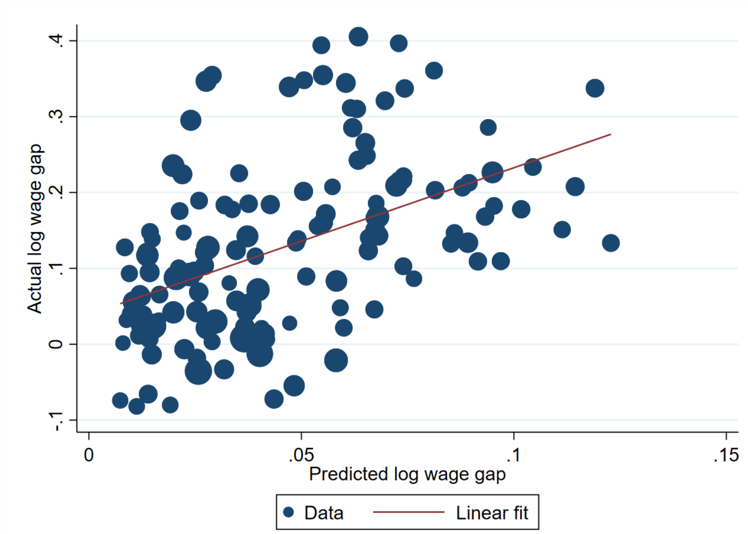


Figure 12: Model predicted gap in log wage vs. data

Note: Note: The figure plots the observed gender gap in log wage against model-predicted gender gap in log wage that is attributed to differential preferences at PUMA level. Each dot represents a unique PUMA location in the New York MSA. The size of each dot represents the number of workers in each PUMA.

Table 1: Summary Statistics

Variables	Men			Women		
	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.
Age	44.034	11.584	3,003,648	44.077	11.623	2,355,573
Married	0.613	0.487	3,003,648	0.525	0.499	2,355,573
Child (< 18)	0.393	0.488	3,003,648	0.384	0.486	2,355,573
High school or lower	0.420	0.494	3,003,648	0.327	0.469	2,355,573
Some college	0.231	0.421	3,003,648	0.262	0.440	2,355,573
College or higher	0.350	0.477	3,003,648	0.412	0.492	2,355,573
Commute time (in hour)	0.436	0.405	3,003,648	0.389	0.356	2,355,573
Hourly wage	30.471	31.348	3,003,648	23.621	21.174	2,355,573

Note: The sample contains full-time workers (i.e., usually worked at least 35 hours per week) aged between 25 and 64 from the 2013-2017 ACS. *Married* is an indicator of being married and spouse being present. *Child (<18)* is an indicator for having a child younger than 18. The variables on education represent the highest educational level. *Commute time* represents one-way commute time measured in hour.

Table 2: Relationship between Wages and Commute Time

Variable	Log (Wage per hour)			
	(1)	(2)	(3)	(4)
Female	-0.227***			
	(0.00256)			
Commute	0.194***	0.119***	0.114***	0.118***
	(0.00449)	(0.00159)	(0.00158)	(0.00163)
Commute × Female	0.111***	0.0474***	0.0477***	0.0535***
	(0.00373)	(0.00229)	(0.00236)	(0.00242)
Observations	5,359,221	5,359,221	5,022,015	5,022,015
R-Squared	0.026	0.379	0.499	0.486
Mean of commute	0.415			
Variance of commute	0.385			

Note: The sample contains full-time workers (i.e., usually worked at least 35 hours per week) aged between 25 and 64 from the 2013-2017 ACS. Commute is one-way commute time in hour. Column 1 does not include any control variables. Column 2 controls for gender-specific dummies for age, race, Hispanic origin, marital status, whether having a child young than 18, education, year, occupation, and residential PUMA. Column 3 furthermore controls for gender- and occupation-specific residential PUMA fixed effects. Column 4 excludes education dummies from Column 3. Standard errors are clustered at the level of residential PUMA. Robust standard errors in parentheses *** p<0.01, ** p<0.05, *p<0.1.

Table 3: Relationship between Wages and Commute Time: By Marital Status

Variable	Log (Wage per hour)				
Residence	All	Chicago	SF	Boston	NY
	(1)	(2)	(3)	(4)	(5)
Panel A: Single					
Commute	0.135***	0.147***	0.151***	0.135***	0.115***
	(0.00308)	(0.0194)	(0.0192)	(0.0193)	(0.0107)
Commute * Female	-0.00444	-0.0148	-0.00892	-0.0164	-0.00214
	(0.00402)	(0.0228)	(0.0226)	(0.0171)	(0.0140)
Observations	1,723,292	50,083	31,084	29,494	119,678
R-Squared	0.513	0.508	0.511	0.497	0.517
Mean of commute	0.407	0.492	0.488	0.479	0.561
Variance of commute	0.376	0.401	0.416	0.386	0.448
Panel B: Married (without spousal controls)					
Commute	0.101***	0.103***	0.136***	0.106***	0.144***
	(0.00181)	(0.00783)	(0.0118)	(0.0122)	(0.00713)
Commute * Female	0.0853***	0.107***	0.0528**	0.0853***	0.0581***
	(0.00301)	(0.0163)	(0.0194)	(0.0208)	(0.0101)
Observations	3,009,954	79,837	45,165	48,860	171,880
R-Squared	0.527	0.533	0.530	0.504	0.539
Mean of commute	0.423	0.505	0.500	0.510	0.580
Variance of commute	0.391	0.410	0.423	0.416	0.474
Panel C: Married (with spousal controls)					
Commute	0.108***	0.115***	0.146***	0.108***	0.151***
	(0.00207)	(0.00840)	(0.0148)	(0.0124)	(0.00787)
Commute * Female	0.0877***	0.105***	0.0570**	0.0857***	0.0600***
	(0.00336)	(0.0196)	(0.0223)	(0.0205)	(0.0116)
Spouse's commute	-0.0247***	-0.0404***	-0.0391***	-0.0151	-0.0261***
	(0.00156)	(0.00813)	(0.0131)	(0.0103)	(0.00522)
Spouse's log working hrs	-0.0708***	-0.0804***	-0.0636***	-0.0746***	-0.0661***
	(0.00146)	(0.00796)	(0.00992)	(0.0109)	(0.00645)
Observations	2,303,726	61,251	34,332	39,709	129,580
R-Squared	0.530	0.534	0.527	0.504	0.540

Note: The sample contains full-time workers (i.e., usually worked at least 35 hours per week) aged between 25 and 64 from the 2013-2017 ACS. Commute is one-way commute time in hour. Panel A includes singles workers (including those who are married but spouses are absent). Panel B and C include married workers whose spouses are present. The estimates in Panels A and B are based on the preferred specification, with the full set of control variables. We furthermore control for spouse's log hours worked and spouse's commute time in Panel C. Standard errors are clustered at the level of residential PUMA. Robust standard errors in parentheses *** p<0.01, ** p<0.05, *p<0.1.

Table 4: Estimates of λ_s

	All	Single	Married	Married w/ children	College	< College
	(1)	(2)	(3)	(4)	(5)	(6)
λ_m	0.2998***	0.3278***	0.2629***	0.2397***	0.2714***	0.3034***
	(0.0063)	(0.0116)	(0.0074)	(0.0089)	(0.0113)	(0.0082)
λ_f	0.3943***	0.308***	0.4341***	0.4365***	0.3744***	0.3922***
	(0.0058)	(0.0110)	(0.009)	(0.0132)	(0.0116)	(0.0092)
$\lambda_f - \lambda_m$	0.0945***	-0.0198	0.1712***	0.1968***	0.1030***	0.0888***
	(0.0086)	(0.016)	(0.0117)	(0.0159)	(0.0162)	(0.0123)
Observations	5,022,013	1,723,290	3,009,952	1,722,902	1,844,511	2,949,875

Note: The sample contains full-time workers (i.e., usually worked at least 35 hours per week) aged between 25 and 64 from the 2013-2017 ACS. Commute is one-way commute time in hour. We use the lower envelope estimator described in the text for the estimation. We choose the reservation utility by selecting the job on the 10th wage percentile around the y-axis. Robust standard errors in parentheses *** p<0.01, ** p<0.05, *p<0.1.

Table 5: Estimates of λ_s by Selected MSA

Residence	NY	Chicago	SF	Boston
	(1)	(2)	(3)	(4)
λ_m	0.3081***	0.3189***	0.3769***	0.3339***
	(0.0257)	(0.0358)	(0.0496)	(0.0375)
λ_f	0.3455***	0.4258***	0.4718***	0.4023***
	(0.0255)	(0.0314)	(0.0471)	(0.0445)
$\lambda_f - \lambda_m$	0.0374	0.1069**	0.0949	0.0684
	(0.0362)	(0.0476)	(0.0684)	(0.0582)
Observations	309,234	137,726	80,580	82,710

Note: The sample contains full-time workers (i.e., usually worked at least 35 hours per week) aged between 25 and 64 from the 2013-2017 ACS. Commute is one-way commute time in hour. The estimates are based on the preferred specification, with the full set of control variables. Standard errors are clustered at the level of residential PUMA. Robust standard errors in parentheses *** p<0.01, ** p<0.05, *p<0.1.

Table 6: Contribution of Gender Differences in Commuting Preferences to the Gender Wage Gap

Residence	Overall	Distance to Downtown (km)			
		(0,5]	(5,15]	(15,30]	30+
Observed gap in log wage	0.1264	0.1722	0.1235	0.1029	0.1929
Model explained gap	0.04261	0.03125	0.01427	0.03778	0.0516
Fraction explained	33.7%	18.2%	11.6%	36.7%	26.7%

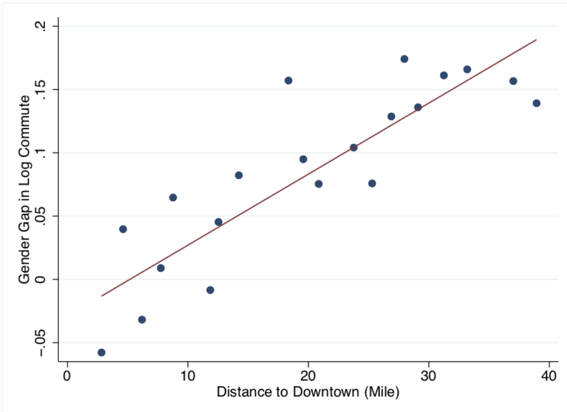
Note: This table shows the results from the decomposition exercises. In the first column, we show the overall observed gap in log wages, the log wage gap that can be explain by gender-specific preferences for commuting, and the fraction of the gap explained by the model. We also conduct the exercise by categorizing workers by their distance to downtown.

Table 7: Effect of Reducing Commute Time on the Gender Wage Gap

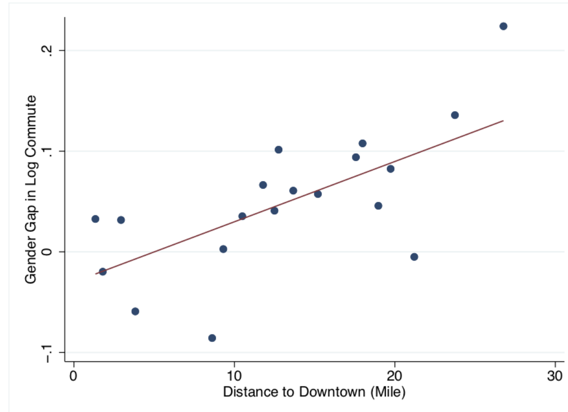
	Reducing Commute Time by			
	10%	20%	50%	90%
Observed gap in log wage	0.1264	0.1264	0.1264	0.1264
Δ Model explained gap	0.003	0.006	0.0139	0.0202
Δ Fraction explained	2.4%	4.7%	11%	16%

Note:

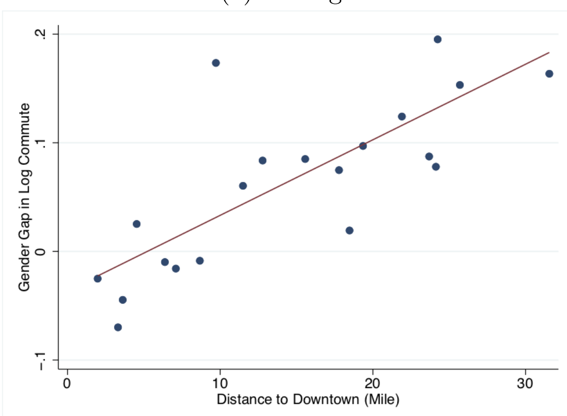
Appendix



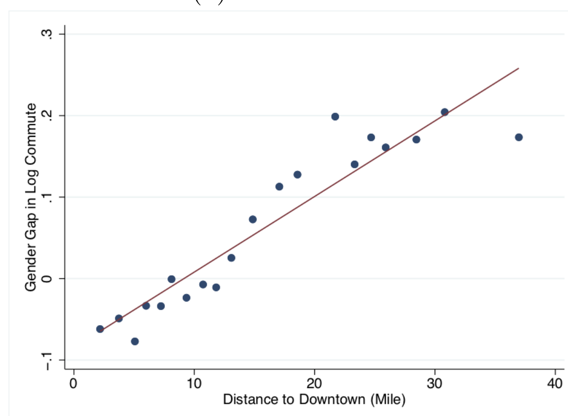
(a) Chicago



(b) San Francisco



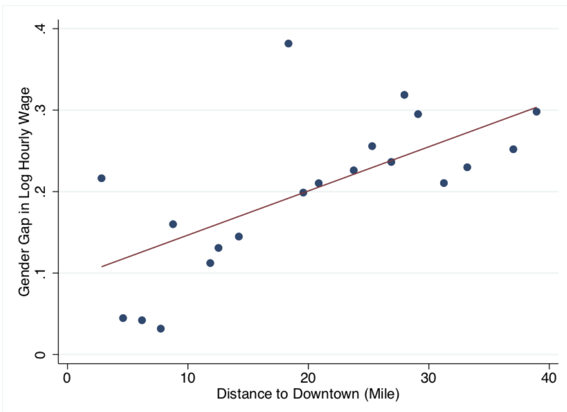
(c) Boston



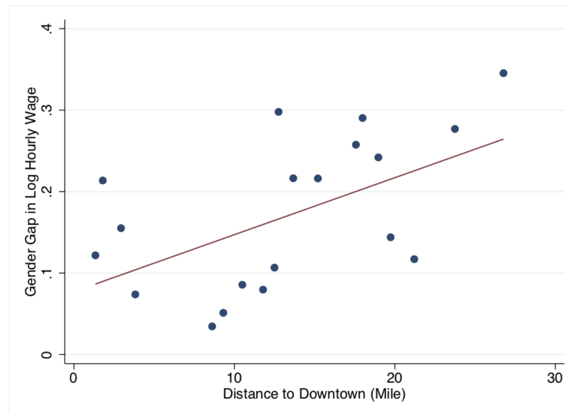
(d) New York

Figure A1: Gender Commuting Gap and Distance to Downtown within Four Metropolitan Areas

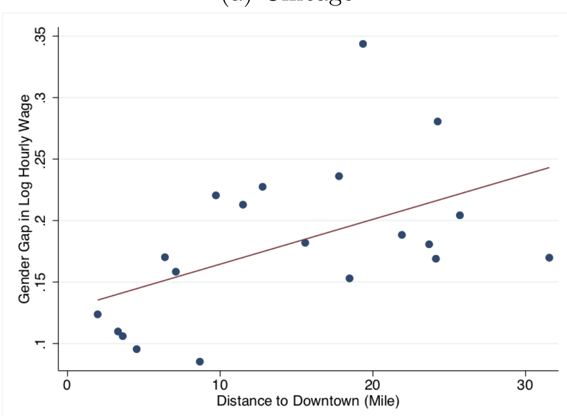
Note: The slope of the fitted line is 0.003 (0.0003) in Panel (a), 0.003 (0.0007) in Panel (b), 0.003 (0.0006) in Panel (c), and 0.005 (0.0003) in Panel (d).



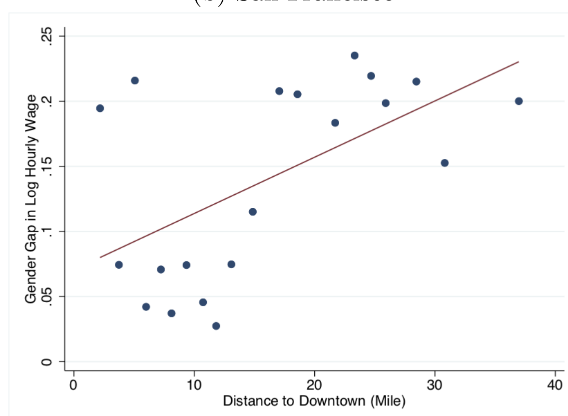
(a) Chicago



(b) San Francisco



(c) Boston



(d) New York

Figure A2: Gender Wage Gap and Distance to Downtown within Four Metropolitan Areas

Note: The slope of the fitted line is 0.0056 (0.0007) in Panel (a), 0.006 (0.0013) in Panel (b), 0.007 (0.0012) in Panel (c), and 0.0093 (0.0006) in Panel (d).

Table A1: Summary Statistics: By Metropolitan Areas

Variables	Men			Women		
	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.
Panel A: Chicago						
Age	43.844	11.465	82,554	43.723	11.648	64,299
Married	0.607	0.488	82,554	0.503	0.500	64,299
Child (< 18)	0.392	0.488	82,554	0.372	0.483	64,299
High school or lower	0.372	0.483	82,554	0.289	0.453	64,299
Some college	0.211	0.408	82,554	0.226	0.418	64,299
College or higher	0.417	0.493	82,554	0.485	0.500	64,299
Commute time (in hour)	0.515	0.411	82,554	0.479	0.398	64,299
Hourly income	34.071	35.336	82,554	26.117	23.602	64,299
Panel B: San Francisco						
Age	43.255	11.445	47,941	43.253	11.700	37,341
Married	0.578	0.494	47,941	0.500	0.500	37,341
Child (< 18)	0.366	0.482	47,941	0.333	0.471	37,341
High school or lower	0.274	0.446	47,941	0.215	0.411	37,341
Some college	0.191	0.393	47,941	0.196	0.397	37,341
College or higher	0.535	0.499	47,941	0.589	0.492	37,341
Commute time (in hour)	0.508	0.426	47,941	0.477	0.411	37,341
Hourly income	44.262	43.149	47,941	35.072	31.436	37,341
Panel C: Boston						
Age	44.276	11.776	48,811	43.920	12.029	38,954
Married	0.611	0.488	48,811	0.522	0.500	38,954
Child (< 18)	0.375	0.484	48,811	0.338	0.473	38,954
High school or lower	0.308	0.462	48,811	0.226	0.419	38,954
Some college	0.166	0.372	48,811	0.186	0.389	38,954
College or higher	0.525	0.499	48,811	0.588	0.492	38,954
Commute time (in hour)	0.511	0.410	48,811	0.479	0.395	38,954
Hourly income	40.152	39.219	48,811	31.303	26.654	38,954
Panel D: New York						
Age	43.927	11.577	180,710	43.849	11.809	149,083
Married	0.577	0.494	180,710	0.464	0.499	149,083
Child (< 18)	0.372	0.483	180,710	0.351	0.477	149,083
High school or lower	0.378	0.485	180,710	0.286	0.452	149,083
Some college	0.182	0.385	180,710	0.196	0.397	149,083
College or higher	0.441	0.496	180,710	0.519	0.500	149,083
Commute time (in hour)	0.588	0.469	180,710	0.550	0.451	149,083
Hourly income	37.835	42.207	180,710	30.093	28.586	149,083

Note: The sample contains full-time workers (i.e., usually worked at least 35 hours per week) aged between 25 and 64 from the 2013-2017 ACS. *Married* is an indicator of being married and spouse being present. *Child (<18)* is an indicator for having a child younger than 18. The variables on education represent the highest educational level. *Commute time* represents one-way commute time measured in hour.

Table A2: Relationship between Wages and Commute Time: By Residential Location

Variable	Log (Wage per hour)					
Residence	Chicago	SF	Boston	NY	Central City	Suburb
	(1)	(2)	(3)	(4)	(5)	(6)
Commute	0.119***	0.148***	0.119***	0.136***	0.0934***	0.120***
	(0.00895)	(0.0103)	(0.00934)	(0.00652)	(0.00576)	(0.00287)
Commute × Female	0.0572***	0.0274	0.0362***	0.0206**	0.0318***	0.0561***
	(0.0127)	(0.0163)	(0.0132)	(0.00849)	(0.00754)	(0.00411)
Observations	137,728	80,582	82,712	309,236	505,006	1,298,516
R-Squared	0.503	0.496	0.491	0.513	0.499	0.505
Mean of commute	0.500	0.494	0.497	0.571	0.467	0.467
Variance of commute	0.406	0.420	0.404	0.462	0.392	0.404

Note: The sample contains full-time workers (i.e., usually worked at least 35 hours per week) aged between 25 and 64 from the 2013-2017 ACS. Commute is one-way commute time in hour. Column 5 restricts the sample to workers living in central city within metropolitan areas and Column 6 restricts the sample to workers living out of central city within metropolitan areas. The estimates are based on the preferred specification, with the full set of control variables. Standard errors are clustered at the level of residential PUMA. Robust standard errors in parentheses *** p<0.01, ** p<0.05, *p<0.1.

Table A3: Relationship between Wages and Commute Time: By Education

Variable	Log (Wage per hour)				
Residence	All	Chicago	SF	Boston	NY
	(1)	(2)	(3)	(4)	(5)
Panel A: High school or lower					
Commute	0.132***	0.138***	0.107***	0.132***	0.122***
	(0.00245)	(0.0189)	(0.0274)	(0.0212)	(0.0106)
Commute * Female	0.0548***	0.0862***	0.00947	0.0113	0.00486
	(0.00459)	(0.0245)	(0.0421)	(0.0308)	(0.0191)
Observations	1,718,786	38,682	15,528	17,565	86,411
R-Squared	0.419	0.430	0.432	0.461	0.439
Mean of commute	0.406	0.479	0.456	0.460	0.541
Variance of commute	0.390	0.400	0.418	0.392	0.453
Panel B: Less than four-year college					
Commute	0.112***	0.113***	0.0864***	0.130***	0.107***
	(0.00332)	(0.0178)	(0.0275)	(0.0362)	(0.0131)
Commute * Female	0.0540***	0.0667**	0.102*	0.0783	0.0500***
	(0.00504)	(0.0315)	(0.0512)	(0.0470)	(0.0171)
Observations	1,016,135	23,338	11,842	10,767	45,010
R-Squared	0.511	0.529	0.505	0.527	0.528
Mean of commute	0.410	0.497	0.473	0.482	0.567
Variance of commute	0.381	0.405	0.419	0.408	0.465
Panel C: Four-year college or higher					
Commute	0.0833***	0.0926***	0.164***	0.0909***	0.139***
	(0.00290)	(0.0120)	(0.0145)	(0.0114)	(0.00999)
Commute * Female	0.0533***	0.0573***	0.0423**	0.0498***	0.0223*
	(0.00374)	(0.0174)	(0.0200)	(0.0164)	(0.0134)
Observations	1,844,513	63,677	46,895	48,077	151,559
R-Squared	0.488	0.462	0.422	0.447	0.460
Mean of commute	0.428	0.516	0.519	0.519	0.594
Variance of commute	0.382	0.410	0.420	0.407	0.465

Note: The sample contains full-time workers (i.e., usually worked at least 35 hours per week) aged between 25 and 64 from the 2013-2017 ACS. Commute is one-way commute time in hour. Panel A includes workers whose highest level of education is high school or lower. Panel B includes workers whose highest level of education is some college (but less than 4 years). Panel C includes workers whose highest level of education is 4-year college or higher. All the estimates are based on the preferred specification, with the full set of control variables. Standard errors are clustered at the level of residential PUMA. Robust standard errors in parentheses *** p<0.01, ** p<0.05, *p<0.1.