

Commuting, Spatial Allocations, and Inequalities

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

This thesis examines the complex relationships between commuting times, wage disparities, gender differences, and urban spatial distribution, through the lens of three interconnected studies. The first chapter investigates the relationship between commuting times, wages, and the gender wage gap, with a focus on controlling for occupational choice endogeneity. Using data from the American Community Survey (ACS) and the Occupational Information Network (O*Net), the study highlights how gender differences significantly influence the positive correlation between commuting time and wages, especially among full-time working homeowners in U.S. cities. Through quantile regression analysis, it reveals that while men's returns on commuting diminish as income rises, the commuting gender gap remains relatively constant across the wage distribution. The second chapter delves deeper into the gendered impacts of commuting on wage disparities, addressing the endogeneity of commuting times. By constructing instrumental variables based on exogenous city characteristics from the 2016 ACS, the study isolates the causal effects of commuting on wages. The findings suggest that marital status drives the gender difference in commuting premiums, with married women and single men demanding higher wages to compensate for longer commutes. This chapter contributes to a broader understanding of wage-commute trade-offs and the socio-economic consequences of commuting time. The third chapter explores the interplay between job flexibility, residential location sorting, and wage determination through a monocentric city model. The model incorporates both high- and low-skilled workers and employs a bid-rent framework to determine housing prices and the spatial distribution of labour. The study finds that high-skilled workers' job flexibility significantly impacts their commuting decisions and urban spatial sorting patterns. In low-flexibility settings, high-skilled workers tend to live near the central business district, earning higher wages to offset the high cost of central real estate and commuting. Conversely, increased job flexibility enables these workers to relocate to more distant, affordable areas, thereby reducing the equilibrium skill premium. Together, these chapters provide a comprehensive analysis of how commuting, gender, and job flexibility interact to shape wage patterns and urban spatial structures in contemporary cities.

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Chapter 1

Commuting Returns and Gender Gaps: Evidence From the U.S. Data

*This chapter investigates the relationship between commuting times, wages, and the gender wage gap, considering the challenge of occupational choice endogeneity. Using data from the American Community Survey (ACS) and the Occupational Information Network (O*Net), the analysis controls for the tasks associated with occupations, rather than the specific job titles. I consider full-time working homeowners in U.S. cities, and show a positive correlation between commuting time and wage. Notably, gender differences play a significant role in this correlation, with women's commuting premiums largely driving this result after taking into account tasks performed in jobs. Applying quantile regression, I estimate the distributional effect of commuting on wages to assess how commuting-wage trade-offs differ across income levels. I find that for men, the return on commuting decreases monotonically as the conditional income level rises, while the commuting gender gap remains relatively constant across the distribution.*

1.1 Introduction

Commuting, especially in metropolitan areas, can be dreadful and have significant negative impacts on the well-being of people who work in cities. According to Chatterjee, Clark, Martin, and Davis (2017), every minute spent on the road increases stress and reduces mental health and satisfaction with leisure time. Moreover, adding 20 minutes of commuting per day makes people as miserable as receiving a 19% salary cut. Despite this, the average travel time to work in major U.S. cities has surged by nearly 20% since 1980 (Ingraham, 2016).¹ In certain urban centers, the average one-way commute time approaches 40 minutes (U.S. Census Bureau, 2017). This phenomenon is not only a daily routine for many but also a subject of considerable academic interest, intersecting the fields of urban planning, transportation, labour economics, and gender studies. Although research in urban

¹According to U.S. Census Bureau, more than 600,000 workers travelled at least 90 minutes each way in 2013 (U.S. Census Bureau, 2013).

planning and transportation has documented significant gender differences in commuting (MacDonald, 1999; Crane, 2007), they have largely bypassed the connection between these patterns and the gender gap in earnings. Conversely, studies in labour economics emphasize the potential role of compensating differentials associated with non-wage amenities (Rosen, 1974) and their contribution to the gender gap (Goldin, 2014), but has, until recently, neglected commuting as a job attribute (Petrongolo & Ronchi, 2020).

An early study that documents the positive effects of commuting on wages using data from the UK is Manning (2003). The study documents that workers working less hours show higher returns to commuting and these workers - in the data - tend to be women. More recently, Le Barbanchon, Rathelot, and Roulet (2021) and Petrongolo and Ronchi (2020) both estimate gender differences in the willingness to pay for a shorter commute, using French data and British data respectively. Importantly, however, women's apparent preference for shorter commutes is not direct evidence of gender-based differences in compensating differentials for commuting. In this regard, Liu and Su (2020) argue that, in the U.S., the geographical distribution of jobs across occupations is heterogeneous and correlated with both the commuting premium in wages and the gender gap, making it a determinant of the wage gap.

This paper investigates the relationship between commuting times and wages, as well as its impact on the gender gap. Previous work has indicated the trade-offs between commuting times and wages and how these might be different for men and women. However, the endogeneity of occupation choices, which can be influenced by personal preferences, societal norms, and economic incentives, presents a significant empirical challenge that has not typically been addressed. Namely, men and women might prefer different types of jobs or sectors, often influenced by non-wage factors such as work-life balance or job flexibility. If women, for example, prefer jobs that allow for shorter commutes but possibly lower wages due to a desire for greater work-life balance, any observed correlation between commuting times and wages could be misleading. It might suggest that shorter commutes are associated with lower wages, but this association could be more about the types of jobs that offer shorter commutes and their typical compensation levels, rather than the commute itself being valued differently by employers.

In response to this complexity, this chapter seeks to dissect and address the endogeneity of occupational choices by introducing controls for the tasks performed within occupations. The rationale of this approach is grounded in the understanding that while occupations may vary, the core tasks they encompass often transcend these occupational boundaries. By focusing on these tasks, this study aims to bypass the potential distortions caused by the endogeneity of occupation selection. Every worker's unique skillset enables them to perform certain tasks, which are, in turn, applicable across a range of occupations. Consequently, controlling for the tasks rather than the job titles offers a more robust framework for analysis, as the tasks are less likely to be influenced by individual preferences about particular job attributes. This method allows for a more accurate comparison of workers performing similar duties, ensuring that the analysis better reflects the impact of commuting on wages without the confounding effects of occupational choice.

I first verify that past findings persist in my sample of more recent U.S. data and

while circumventing the problem of occupational choice. I then apply a quantile regression technique to estimate whether there is a differential effect of commuting along the wage distribution. My initial results are in line with most studies, such as Manning (2003), where a positive correlation between commuting time and wage is found. This positive correlation between commuting and wages is mainly driven by women’s commuting premiums, even after I control for job tasks. My results also indicate that the commuting return monotonically decreases as we move toward the upper levels of the wage distribution while keeping other socio-economic factors constant. However, the commuting gender gap - or the difference in the returns to commuting attributed to gender - largely remains the same across the distribution.

This study uses data from the American Community Survey (ACS), which reports information on commuting times together with an extensive array of demographic and socioeconomic information. I focus on full-time working homeowners in U.S. cities with the purpose of reducing the heterogeneous effects of commuting. Firstly, owning a home typically comes with significant fixed costs - such as mortgage payments, property taxes and maintenance costs. The commitment to a full-time job also introduces rigidity in terms of increasing labour supply. Secondly, by restricting the sample to urban areas, the study effectively narrows down the analysis to more homogeneous commuting patterns, infrastructure, and job types. Consequently, the findings are more directly applicable to the urban context, where commuting plays a significant role in daily life, and avoids the ambiguities that might arise from considering a more heterogeneous sample.

The structure of this chapter is as follows. Section 1.2 reviews the relevant literature, and Section 1.3 discusses the methodology. While Section 1.4 provides a detailed description of the study sample, Section 1.5 presents the empirical results from my analysis. Finally, Section 1.6 concludes.

1.2 Literature Review

The study of urban labour economics can be dated back to Lucas and Prescott (1978). Since then, researchers have paid particular attention to understanding the formation of cities and economic agglomerations. Many of them point out the importance of commuting time (Hamilton & Röell, 1982; K.-R. Ma & Banister, 2006; Zenou, 2009). The cost of travelling, which is often reflected by travel duration, has been proven to be a substantial factor that not only reflects the efficiency of the labour market but also impacts people’s welfare (Arnott, De Palma, & Lindsey, 1994; Cervero, 2001; Stutzer & Frey, 2008). Since the proposal for the Rosen-Roback model (Rosen, 1974; Roback, 1982), people have started to consider commuting costs as one of the main amenities that contribute to compensating wage differentials. In theory, rational individuals would only tolerate longer commutes if being compensated by a better job with higher wages (Chatterjee et al., 2017). However, depending on an individual’s socioeconomic status, the preference and opportunity cost for commuting are likely to be different. For instance, many studies reveal that females are more sensitive to commuting than males, and women with kids tend to travel the least to work (J. Roberts, Hodgson, & Dolan, 2011; McQuaid & Chen, 2012). Both scenarios

indicate that women, especially those with children, need to be compensated more for longer commutes. Thus, the journey to work likely involves heterogeneous compensating effects across gender. In fact, many studies focusing on transportation have found evidence of commuting gender differentials. For example, Wyly (1998) noticed the more localized commutes by women, especially in urban areas. In a more recent paper, Crane (2007) uses panel data and finds that the shorter commute trend for women stubbornly persists despite females' increasing involvement in the economy. In theory, if the commute time is known *ex-ante*, then the individual is ultimately choosing how long to commute by accepting a job offer. Thus, gender commute differences should contribute, at least partially, to the gender pay gap through compensating differential.

The gender wage gap has always been an important topic in labour economics, and researchers have been investigating it for decades (Blau & Kahn, 2017). Goldin (2014), among other studies, points out the substantial trend of convergence in earnings across gender. However, the overall wage gap remains substantial, and human capital variables explain little of it (Blau & Kahn, 2008, 2017). A number of early studies claim that the unexplained gap is due to gender discrimination (Madden, 1973; Darity & Mason, 1998; Gibelman, 2003; Lips, 2013). For instance, Drolet (2002) pointed out that women's lifetime working experiences are significantly less than men's. Other studies have documented the persistent occupational segregation of women in lower-paid jobs (Petersen & Morgan, 1995; Darity & Mason, 1998; Anker, 1998; Charles & Grusky, 2005). In particular, Olivetti and Petrongolo (2008) argued that due to workforce frictions and discrimination, women tend to self-select into occupations with lower wages, and the differences in female employment could partly explain the gender pay gap across countries. Nevertheless, since Goldin (2014), recent literature also emphasizes the critical role of compensating differential (Blau & Kahn, 2017). Specifically, women seem more willing to bear wage penalties in exchange for job amenities such as flexibility and low pressure. This chapter seeks to provide a more systematic analysis of gender compensating differential from the commuting perspective.

On top of past empirical studies, a number of theories accounting for the interaction between commuting and labour markets have been proposed; see Zenou (2009) for a comprehensive review. In particular, researchers believe that the commuting cost is an essential factor that influences a wide range of labour market outcomes, including job polarization (David & Dorn, 2013), labour supply (Wales, 1978), and working effort (J. N. Van Ommeren & Gutiérrez-i Puigarnau, 2011; Ross & Zenou, 2004). Furthermore, many researchers have investigated the connection between commuting and wages. Much empirical evidence has been presented to demonstrate a positive relationship between the two. For example, Manning (2003) uses two datasets from the U.K. and finds a robust positive correlation between travel time and earnings. In a more recent study, Mulalic, Van Ommeren, and Pilegaard (2013) demonstrates a 0.15% wage increase after three years with 1 kilometre-longer commuting distance. Nonetheless, these studies tend to focus on pooled data with large scales of labour market endogeneity, which has several downsides. For example, the model may not be able to accurately capture the underlying relationships between wages and commuting times due to the presence of high variability, and the estimated coefficients may not accurately represent the true effects. In this paper, the study sample is much more restricted for the purpose of generating more credible results.

In recent years, researchers have started to look at the connection between commuting and the gender gap. For example, Le Barbanchon et al. (2021) estimate that 14% of the residualized gender wage gap comes from the differences in commute valuation; while Liu and Su (2020) find that commuting choices could account for about 21% of the observed gender wage gap. Similarly, Velásquez (2022) states that the gender earnings gap could encounter a 12% reduction if the researchers take into account the household commuting mechanism. These research have made significant strides in understanding the impact of commuting on gender gaps by leveraging structural models to simulate potential outcomes. Building upon this foundation, my approach complements these efforts with a detailed empirical analysis. I aim to utilize direct evidence from the data to delve deeper into this relationship, add a new dimension to the existing literature and provide fresh insights. I also adopt the quantile regression technique and focus on the distributional effect of commuting rather than the mean effect (Koenker & Hallock, 2001). To the best of my knowledge, quantile regression has never been used to demonstrate the heterogeneous effects of commuting across the wage distribution.

It should be mentioned that several studies have tried to tackle the endogeneity problem associated with commuting and make casual inferences accordingly. For example, Travisi, Camagni, and Nijkamp (2010) have determined the causal relationships between travel time and urban sprawl using Causal Path Analysis. Using the fixed effects model with longitudinal data, studies like Jin, Kim, and Jin (2022), X. Wang et al. (2023) and Asongu and Salahodjaev (2022) demonstrate an increased commuting time is negatively associated with workers' life satisfaction. Tigre, Sampaio, and Menezes (2017) use distance to the closest schools as an instrumental variable for commuting time to analyze how commuting duration impacts students' school performance. Multiple studies have utilized instrumental variables to examine the relationship between commuting time and labour supply. For example, Gimenez-Nadal and Molina (2011) use housing prices as the instrument, while Farré, Jofre-Monseny, and Torrecillas (2020) exploit the exogenous variation of city shapes. However, to the best of my knowledge, very little empirical work has been done to address the endogeneity of commuting when looking at its impact on wages. Although addressing the endogeneity of commuting is beyond the scope of this chapter, I use the empirical evidence presented in this chapter to motivate my further analysis in Chapter 2, which focuses on the causal relationships between commuting time and wages.

1.3 Methodology

1.3.1 Hedonic Wage Regressions

I start by showing the importance of controlling for different factors in the relationship between wages and commuting times. I perform four OLS regressions with clustered standard errors on the city of work. Equation (1.3.1.1) displays the generic form of all regressions:

$$\log w_i = \beta_0 + \beta_1 comm_i + \gamma^\top x_i + \epsilon_i. \quad (1.3.1.1)$$

The control variables included in x_i for each regression are as follows:

1. year
2. year + city of work
3. year + city of work + employer controls
4. year + city of work + employer controls + demographic controls

The employer controls include industry and class of worker; and demographic controls include gender, age, marital status, race, educational attainment, the number of children and the five occupational task indices.² Marital status and children variables are interacted with gender.

I refer to the above four regressions as base models, and they provide insights into how estimated commuting returns vary with different sets of controls.

To account for heterogeneity in commuting cost, I also perform the regression analysis again and interact commuting time with gender. Essentially, I allow men and women to have different commuting returns. The model can be expressed as follows:

$$\log w_i = \beta_0 + \beta_1 comm_i + \beta_2 female_i + \beta_3 comm_i \times female_i + \gamma^\top x_i + \epsilon_i, \quad (1.3.1.2)$$

where w_i is the hourly wage rate, $comm_i$ is the commuting time, $female_i$ is the individual's female indicator, and x_i contains year, city of work, employer and demographic controls (except gender). It is worth defining a few key terms based on the coefficients of Equation 1.3.1.2: β_1 is the marginal effect of commuting time for males; β_2 represents the non-commuting gender gap and β_3 the commuting gender gap. Consequently, $\beta_1 + \beta_3$ indicates the marginal effect of commuting time for females, and $\beta_2 + \beta_3$ reveals the (total) gender gap associated with one hour of commute time. Note that by including the interaction term between commuting time and gender, I have ultimately decomposed the total gender gap into two parts: commuting-related and commuting-unrelated.

To further understand the nature of the gender heterogeneity regarding the commuting-wage association, particularly for female workers, I perform subsequent OLS regression with the female sub-sample. In particular, I interact the commuting time with different variables. The model can be expressed as follows:

$$\log w_{i,f} = \beta_{0,f} + \gamma^\top x_{i,f} + \beta_1 \cdot comm_{i,f} + \sum_{j=1}^J \delta_j \cdot (comm_{i,f} \times \omega_{i,f,j}) + \epsilon_{i,f}, \quad (1.3.1.3)$$

where $\omega_{i,f,j}$ represents individual variables that I am interested in exploring more, including class of worker, industry, age, marital status, education, and the indicator of having young children. The coefficients δ_j measure how much more (or less) commuting compensation certain groups of women receive by spending one more hour commuting to their workplace.

²The occupational task indices are based on the similar system proposed by D. H. Autor, Levy, and Murnane (2003). I provide a detailed explanation in Section 1.4.1.

1.3.2 Quantile Regressions

In the second part of my analysis, I employ the quantile regression technique to explore how commuting times affect wages across different points of the income distribution (Koenker & Hallock, 2001). This approach allows me to investigate how the wage-commuting relationship varies for individuals situated at different percentiles of the wage distribution. Unlike OLS, which only captures the average effect, quantile regression provides a more nuanced view by revealing how returns to commuting may differ across the income spectrum, potentially uncovering patterns that would otherwise be obscured.

Quantile regression, as indicated by its name, aims to model the relationship between a set of predictors and specific percentiles of a target variable. The idea was first introduced by Koenker and Bassett Jr (1978) and the authors seek to extend the ideas of analyzing percentiles of the population to the estimation of conditional quantile functions. In other words, they explore ways to model the quantiles of the conditional distribution of the response variable and express that as functions of observed independent variables.

The benefit of using quantile regression is two-fold. First, quantile regressions do not make any assumptions about the distribution of the dependent variable, making them particularly useful when dealing with skewed data. In contrast, OLS analysis assumes normally distributed and homoscedastic errors. If the dependent variable is skewed, as is the case in my analysis where the estimated hourly wage rate distribution shows a heavy right tail (Figure 1.1), this assumption may be violated. While OLS can still provide valuable insights into the mean effect of commuting on wages, it may not fully capture the nuances of the wage distribution, especially in the tail end. My quantile regression analysis thus complements the OLS findings and allows me to gain a more comprehensive understanding of the wage-commuting correlation.

Secondly, quantile regression tends to be more robust and less sensitive to outliers as the score function assigns lower weights to observations that are further away from the specified quantile. This robustness is particularly important when dealing with heavily skewed dependent variables, which are more likely to contain extreme values or outliers. These outliers can disproportionately influence OLS results, distorting estimated coefficients and leading to inaccurate predictions. Traditional linear regressions, which focus on estimating conditional *means*, often overlook the need to estimate separate quantiles for non-normally distributed dependent variables. In contrast, quantile regression allows for the estimation of conditional quantile functions, offering a more appropriate and insightful approach when the normality assumption is violated. This method is particularly valuable for my research as it enables a deeper investigation into the distributional effects of commuting times.

My two sets of quantile regression models for the τ^{th} quantile can be expressed as follows:

$$Q_{\log w_i | x_i, comm_i}(\tau) = \beta_{0,\tau} + \beta_{1,\tau} comm_i + \gamma_\tau^\top x_i + \epsilon_i. \quad (1.3.2.1)$$

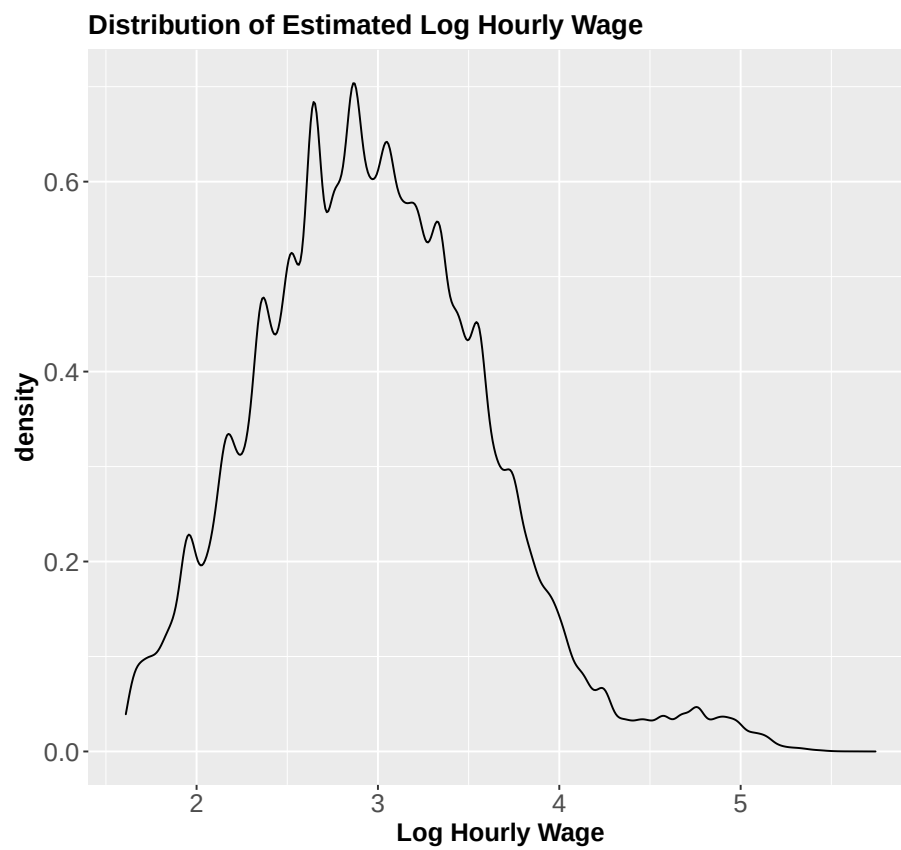


Figure 1.1: Distribution of Estimated Log Hourly Wage

and

$$Q_{\log w_i | x_i, comm_i}(\tau) = \beta_{0,\tau} + \beta_{1,\tau} comm_i + \beta_{2,\tau} female_i + \beta_{3,\tau} comm_i \times female_i + \gamma_\tau^\top x_i + \epsilon_i, \quad (1.3.2.2)$$

where w_i is the hourly wage rate, $comm_i$ is the commuting time, $female_i$ is the individual's female indicator, and x_i contains year, city, employer and demographic controls similar to those of the OLS regressions.

I acknowledge that one drawback of my analysis is that I do not consider the endogeneity of commuting times, which could stem from the simultaneous causal impact between wages and commuting and people's self-selection into cities with various traffic network patterns. To handle heterogeneity in commuting times and identify the causal effect of commuting on wages, I need to find an instrumental variable (IV) that is correlated with commuting time, but uncorrelated with the error term of my regressions. In Chapter 2, I discuss several potential instruments and report the IV estimation results.

1.4 Study Sample: ACS

1.4.1 Overview

The data used in this study comes from the public version of the American Community Survey (ACS) 2012-2017.³⁴ ACS is an ongoing survey conducted every year by the U.S. Census Bureau (U.S. Census Bureau, 2018b). It is one of the largest household surveys in U.S.⁵ and covers a variety of topics, including educational attainment, income, migration, and employment (U.S. Census Bureau, 2018c, 2019b). The participation of ACS is mandatory (U.S. Census Bureau, 2019a). Hence, the sample is relatively representative.

The public version contains a sample of the actual responses of ACS and covers approximately one percent of the United States population (U.S. Census Bureau, 2018a). My study sample includes people between the ages of 25 and 60 who are currently employed. To avoid extreme values that could introduce measurement errors, I set the minimum hourly wage for the study sample to be \$5.⁶ Further restrictions are described in the following subsections.

Commuting holds different implications for workers in rural versus urban areas. While rural commuting often involves longer distances between towns and regions, urban commuting typically covers shorter distances but can be much more time-consuming due to

³The data was downloaded from IPUMS USA, a website managed by the University of Minnesota and provides access to integrated samples from ACS (IPUMS USA, n.d.-b)

⁴I chose the period 2012 - 2017 due to the consistency of geographical boundaries and the occupation classifications. Between the years 2012 and 2017, the Public Use Microdata Areas (PUMAs) are identified based on the 2010 PUMA definition (IPUMS USA, n.d.-a), and the person's primary occupation is classified according to the 2010 Standard Occupational Classification (IPUMS USA, n.d.-e).

⁵According to U.S. Census Bureau, over 3.5 million households across the country are contacted every year to participate in the ACS (U.S. Census Bureau, 2019b).

⁶To account for inflation, all estimated wages have been converted back to the value of the year 1999. The federal minimum wage in 1999 was \$5.15/hour.

severe congestion in metropolitan areas (Coombes & Raybould, 2001; Chodur, Ostrowski, & Tracz, 2016; Lucinda, Moita, Meyer, & Ledo, 2017). Given these differences, analyzing data from both rural and urban commuters could lead to skewed analytical results, particularly since urban workers often experience greater income inequalities and a larger variance in wages compared to their rural counterparts (Morrill, 2013). To avoid such disproportionate effects and ambiguous findings, this study focuses exclusively on individuals who work in metropolitan areas, where the trade-offs between commuting time and wages are more pronounced and relevant to the research question.

To accurately capture urban labour markets, I utilize geographical information from ACS, which provides data on individuals' places of work.⁷ This data is organized into contiguous, non-overlapping geographic units, enabling the definition of metropolitan-area-wide labour markets. For this analysis, I focus on metropolitan areas — regions consisting of a large urban core and surrounding communities with strong economic and social integration — that have a working population⁸ greater than 150,000 as of 2012.⁹ This threshold ensures that the analysis is concentrated on significant urban centers where the commuting-wage trade-offs are most relevant.

The reported commuting time in the ACS data refers to “travel time to work,” which measures the duration of the commute from home to work in minutes. For the purposes of this study, I calculate the total round-trip commuting time in hours based on this data. Throughout this paper, “commuting time” will refer to this calculated two-way duration. I also truncate the sample at a maximum of 3 hours of commuting per day to eliminate disproportional effects caused by extremely long commutes.

To ensure consistency in industry classifications across all cycles of ACS, I use the 1990 Census Bureau Industrial Classification scheme to control for industries. According to IPUMS USA (n.d.-d), the 1990-classification-based variable is the preferable long-term industry control for samples from 1980 onward. The total number of industries being controlled for my sample is 224.

Given the focus on the trade-offs between wages and commuting times, I exclude individuals who work in family businesses without pay, as well as self-employed workers, who typically have more flexible schedules and distinct labour market behaviours (Gimenez-Nadal, Molina, & Velilla, 2018). My sample includes employees from both the private and public sectors, ensuring a comprehensive analysis of the workforce.¹⁰ Furthermore, it is crucial to differentiate between part-time and full-time workers, as their labour market decisions often differ significantly. Part-time workers, in particular, tend to have more flexible schedules with shorter working hours, which likely reduces the impact of daily commuting on their overall work experience. According to the U.S. government, a full-time employee is defined to be anyone who works an average of at least 30 hours per week for more than

⁷<https://usa.ipums.org/usa/volii/10pwpuma.shtml>

⁸The working population is estimated by summing the frequency weights of observations that work in a particular metropolitan area.

⁹Data comes from ACS. Refer to Appendix A for the full list of included metropolitan areas and their estimated working populations.

¹⁰Private sector includes employees of private companies, businesses, or non-profit organizations; public sector includes local, state or federal government employees.

120 days in a year.¹¹ Due to the lack of job tenure information in the U.S. data, I select employees who work at least 30 hours per week and at least 50 weeks within a year and define them as full-time workers. I further convert the reported annual wage income in ACS to the hourly rate.¹²

To further standardize the sample and eliminate potential mobility heterogeneity, I restrict the analysis to homeowners. Housing mobility can significantly impact the opportunity cost of commuting, and homeowners generally face higher costs of relocation compared to renters. By focusing on homeowners who work full-time, I concentrate on individuals with higher opportunity costs for changing jobs or relocating, ensuring that the commuting-wage trade-offs analyzed are more consistent across the sample.

A critical component of my analysis involves controlling for occupational tasks to mitigate potential biases related to occupational choice. Individuals' primary occupations are categorized by the 2010 Standard Occupational Classification (SOC) system¹³ across all years in my data. However, controlling directly for occupation in my analysis could introduce omitted variable bias, as occupational choices are rarely random. The type of occupation may be correlated with unobserved factors, such as individual preferences and abilities, leading to the issue of occupation endogeneity and potentially biasing the regression results. To mitigate this selection bias, I replace the occupation indicators with *occupational task indices*, which consider the types of tasks required to perform duties associated with different types of jobs. In particular, for each occupation, five types of task requirements are considered: non-routine analytical tasks, non-routine interactive tasks, non-routine manual, routine manual and routine cognitive tasks. This approach was developed by D. H. Autor et al. (2003), where the authors use these indices to study how computerization changes the skill demands for jobs over time. The system has since been widely used to analyze occupational diversities (Warman & Worswick, 2015; Yamaguchi, 2012). For the purpose of this study, I take advantage of the fact that these five types of occupational task requirements are mutually exclusive from one another and measure somewhat exogenous characteristics of an occupation. Individuals may choose which occupation they want to work in, but they typically do not choose the task requirements. Therefore, by controlling occupation this way, I have replaced the endogenous occupation with task requirements that are more exogenously determined. In other words, I am comparing people who face similar task requirements at work, no matter what their actual occupation is. I believe these indices are independent of people's occupational preferences and thus provide me with better occupational controls.

I adopt a similar strategy as Warman and Worswick (2015), where the SOC codes in the data are matched with the Occupational Information Network (O*NET) reference codes and the corresponding skill requirement scales.¹⁴ The relevant job requirements are

¹¹<https://www.healthcare.gov/glossary/full-time-employee/>; <https://www.irs.gov/affordable-care-act/employers/identifying-full-time-employees>

¹²I divide the reported amount by the product of working hours per week and 50, assuming that most full-time workers work 50 weeks every year and enjoy at least 2 weeks of vacation.

¹³<https://usa.ipums.org/usa-action/variables/OCCSOC>

¹⁴The O*NET database contains standardized and occupation-specific information on the tasks required for a given occupation, through which I can infer the occupational task indices. The SOC to O*NET

divided into the five task groups, and a Principal Component Analysis (PCA) is executed to reduce the dimension of the data to 5.¹⁵ The estimated loading factors are then used to calculate the indices of each of the five groups for a given occupation, which in turn serve as the occupational controls in my regressions.

1.4.2 Summary Statistics

My final study sample contains 1,574,673 observations. Refer to Appendix C for the variable descriptions. Table 1.1 presents the weighted summary statistics for the study sample. The mean commuting time is 0.95 hours, or about 57 minutes, and males tend to commute longer than females. Most of the observations are Caucasians, and more than 80% of the study sample works in the private sector.

Table 1.1: Summary Statistics

<i>Continuous Variables</i>				
	Min.	Median	Max.	Mean
Log Estimated Hourly Wage	1.61	2.95	5.74	2.94
Commuting Time	0	0.83	3	0.95
Commuting Time - Male	0	1	3	0.98
Commuting Time - Female	0	0.83	3	0.91
Age	25	46	60	43.8
Number of Children	0	1	9	1.02
<i>Discrete Variables (%)</i>				
Gender	Male: 57.06		Female: 42.94	
Marital Status	Married: 67.4			
Class of Worker	Private: 80.72			
Race	Caucasian: 74.63		African-American: 10.35	
Education	< High School: 5.34		High School: 19.86	
	Associate ⁴ : 29.56		Bachelor: 28.37	
	Graduate: 16.86			

¹ Data Source: ACS 2012-2017.

² Wages are adjusted to the 1999 level.

³ The commuting time is converted into two-way in hours.

⁴ In the U.S., associate's degrees are available at various types of colleges, including community colleges, junior colleges and technical colleges, affiliated colleges of universities and university institutes. It typically takes two years full-time to complete an associate's degree.

reference comes from <https://www.onetcenter.org/taxonomy.html>

¹⁵For the list of job requirements included in the PCA, refer to Appendix B.

Figure 1.2 illustrates the unconditional commuting time distribution for the study sample. The majority commute between 0.5 to 1.5 hours every day.

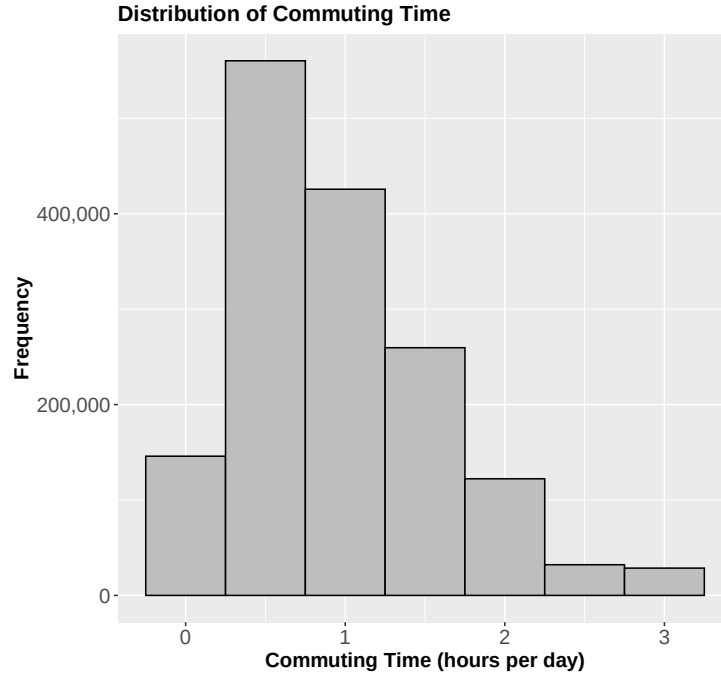


Figure 1.2: Unconditional Distribution of Commuting

1.5 Empirical Results

1.5.1 Wages and Commuting Times - OLS

This section documents estimates of the correlation between commuting times and the logged hourly wage rates. Note that I employ clustered standard errors based on the place of work. This approach accounts for the possibility that workers in the same location may share unobserved factors or face similar conditions that could affect them in similar ways. By clustering the standard errors, the analysis becomes more robust to the influence of intragroup correlation, ensuring that the regression estimates remain reliable and that the conclusions drawn from the data accurately reflect the underlying relationships.

Base Models

I start by showing the importance of controlling for different factors in the relationship between wages and commuting times. I perform the four base OLS regressions mentioned in Section 1.3.1, model (1.3.1.1). The base model results are summarized in Table 1.2.

The model in the first row only includes the year control and aims to provide an idea about the overall association between commuting and wages. The result suggests that

one more hour of commuting is associated with a 9.3% increase in wages. To eliminate variations due to geographical locations, I add controls for the workplace in the second model. Controlling for the city of work reduced the coefficient by over 30% and put the association at 6%, which indicates a significant variation in the commuting-wage correlation across geographical locations. In the third regression, I further investigate how important the type of job is in this relationship and add controls for industry and the class of worker. These control variables reduce the commuting-wage association by another 50% to a 3.3% increase in wages with one more hour of commuting. This means that industry and class of worker also play an important role in influencing the relationship between commuting and wages. Finally, personal controls are added to eliminate effects from different demographics such as gender, age, education attainment and marital status. Again more than 50% of the correlation can be explained by demographic differences, and now an additional hour of commuting time is associated with a 1.5% increase in wages. In summary, it appears that even though the scale of the estimated coefficient shrinks significantly when controlling for more variables, commuting time remains positively and significantly correlated with wages.¹⁶

Table 1.2: Base Models Estimated Results

<i>Dependent Variable: Log Hourly Wage Rate</i>				
Year	City	Employer Controls	Personal Controls	Estimates (β_1)
✓				0.093*** (0.016)
✓	✓			0.06*** (0.011)
✓	✓	✓		0.033*** (0.01)
✓	✓	✓	✓	0.015** (0.01)

¹ *p<0.1; **p<0.05; ***p<0.01

² Data Source: ACS 2012-2017; 68 cities.

³ Employer controls include industry and class of worker; and demographic controls include gender, age, age squared, marital status, race, education attainment, any children under 14 indicator and occupational task indices. Marital status and children indicator variables are interacted with gender.

⁴ All regressions are estimated using OLS with clustered standard errors regarding working places.

⁵ Full regression estimates are available in Appendix D.

¹⁶In Manning (2003), the estimated coefficients are 0.069 for the regression including all controls, which is much higher than my estimates. This is likely due to the fact that the two studies utilize different data sources (Manning (2003) uses data from the United Kingdom).

Interaction between Commuting and Gender

To account for heterogeneity in commuting cost, I perform the regression analysis again and interact commuting time with gender (model (1.3.1.2)). Essentially, I allow men and women to have different commuting returns. The results are summarized in Table 1.3. Note that the estimated coefficient on commuting becomes insignificant. This means that for male workers, adding one more hour of daily commute has no effect on their wage rates, a significant difference from the previous analysis. The non-commuting gender gap (β_2) is estimated to be -0.141 , meaning that without considering commute, females earn approximately 14% less than men. However, the commuting gender gap (β_3) is positive and estimated to be 0.025 , meaning that compared to male commuters, female commuters earn about 2.5% more for each hour of commute. Consequently, the female commuting return equals 0.03 , and the gender gap associated with one hour of commute is estimated to be -0.116 . In other words, I have overestimated the gender gap without considering females' commuting returns.

These results suggest that the positive correlation I got from Table 1.2 is primarily driven by women's commuting premiums, not men's. Moreover, the female's excess return on commuting helps to reduce the gender gap.

Table 1.3: Base Model with Interaction Estimated Results

	Estimation
Marginal Effect of Commuting for Men (β_1)	0.004
Non-Commuting Gender Gap (β_2)	-0.141^{***}
Commuting Time $\times$ Female (β_3)	0.025^{***}
Marginal Effect of Commuting for Women ($\beta_1 + \beta_3$)	0.030^{***}
Gender Gap for One Hour of Commute Time ($\beta_2 + \beta_3$)	-0.116^{***}

¹ * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

² Data Source: ACS 2012-2017; 68 cities.

³ The regression is based on Model 4 from the base regressions.

⁴ The regression is estimated using OLS with clustered standard errors regarding work places.

⁵ Full regression estimates are available in Appendix D.

Female Sub-Sample

Based on the previous analysis, it seems that females are the main driving force behind the positive commuting returns. However, this raises an important question: why is this the case? To further understand the nature of females' higher commuting returns and identify the reasons behind it, I perform subsequent OLS regression with the female sub-sample (model (1.3.1.3)). The results are displayed in Table 1.4. For the purpose of identifying women with the highest commuting returns, I display all essential interaction terms, as

well as the two industry categories that have positive and significant coefficients. Note that the task requirement indices estimates are also included, which are all significantly correlated to wages.

Table 1.4: Female Sub-Sample Estimations

	Estimation
CT (Commuting Time)	−0.06***
CT × Private Sector	0.01
CT × IND: Apparel/Accessories	0.066***
CT × IND: Department Stores	0.064***
CT × Age	0.002***
CT × Married	0.018***
CT × Children ≤ 14 Years Old	0.017***
CT × Less than High-School	−0.003
CT × Associates Degrees	0.007**
CT × Bachelor’s	−0.005
CT × Graduate Degrees	−0.03***
NRA Index	0.087***
NRI Index	−0.059***
NRM Index	0.021***
RM Index	−0.013***
RC Index	0.063***
Year FE	Y
City FE	Y
Industry FE	Y
Age ²	Y
Race FE	Y

¹ *p<0.1; **p<0.05; ***p<0.01

² Data Source: ACS 2012-2017; 68 cities; female only

³ Commuting time is interacted with class of worker, industry, age, marital status, educational attainment and whether the individual has children less than or equal to 14 years old.

⁴ The base group is single caucasian women working in elementary and secondary schools located in New York-Newark-Jersey metropolitan area and having high-school diplomas.

⁵ The regression is estimated using OLS with clustered standard errors regarding working places.

⁶ The male sub-sample regression estimates are available in Appendix E.

The first thing worth mentioning is that the commuting time itself is negatively correlated with wages, which means that for the base group: single caucasian women working in

elementary and secondary schools located in New York-Newark-Jersey metropolitan area and having high-school diplomas,¹⁷ one more hour of commuting is associated with a 6% decrease in wages. This piece of evidence also supports my hypothesis that the group of women having positive commuting returns is being adequately captured in the interaction terms I investigated in Section 1.3.1.

Based on the results from the industry interaction terms, it seems that women working in industries of apparel/accessories and department stores are the ones with the highest commuting compensations, earning about 6% more wages by commuting one more hour. This could be because these industries tend to be located in city centres where the population is dense, which makes commuting harder and more costly.

Married females and those who have young children at home also need to be compensated more for commuting. For married women, one more hour of commuting is associated with about a 1.8% wage increase. For women with children under the age of 14, 1.7% is added to this correlation. The literature has consistently found that women tend to take on more part of housework and childcare responsibilities. For example, Craig and Mullan (2011) analyzes the time-use data from Australia, Denmark, France, and Italy and conducts a cross-national comparison to examine differences in the amount of time mothers and fathers spend on childcare. The study finds that mothers in all four countries spent significantly more time on childcare than fathers did, even in the most egalitarian country Denmark. Therefore, it is likely that the higher commuting compensation for married women and those with young children is a result of the higher family responsibility women bear at home.

Moreover, older females seem to assign greater importance to commuting compared to younger ones. Although not a big increase, 10 years of age is still associated with a 2% significant increase in wage rates when commuting one more hour.

The estimated coefficients that are not significant or even negative are also interesting and worth mentioning. For example, being in the private sector does not make a difference in terms of wage-commuting correlation. Similarly, compared to women holding high school diplomas, having a less than high-school degree or bachelor's degree does not have a significant impact on women's hourly commuting premium. Interestingly, women having associate degrees tend to have a slightly higher commuting premium (0.7% and significant at 5% level). Moreover, having a graduate degree lowers women's commuting premium by 3%. The lower commuting return for highly educated women could be explained by other occupational perks, such as higher chances of working remotely or having more job authority (Bick, Blandin, & Mertens, 2020).

The analysis underscores substantial differences in commuting premiums between genders. With this in mind, I further examine how commuting impacts individuals across different income levels.

¹⁷Only 104 observations belong to the base group, about 0.02% of the total female sample.

1.5.2 Quantile Regressions

The quantile regression results are presented in Table 1.5. Due to the large sample size, I use the Frisch–Newton interior point algorithm when fitting the model (Portnoy & Koenker, 1997). The standard error is estimated using a non-parametric approach proposed by Powell, Barnett, and Tauchen (1991). As stated by Angrist, Chernozhukov, and Fernández-Val (2006), the kernel estimator is consistent over a closed interval of a specified quantile even when the model is misspecified.

Table 1.5: Quantile Regression Estimated Results

<i>Dependent Variable: Log Hourly Wage Rate</i>					
	$\tau = 0.1$	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$	$\tau = 0.9$
Marginal Effect of Commuting	0.033*** (0.001)	0.027*** (0.001)	0.019*** (0.001)	0.009*** (0.001)	−0.005*** (0.001)
Effect of Commuting - Male	0.025*** (0.002)	0.016*** (0.001)	0.007*** (0.001)	−0.002 (0.001)	−0.016*** (0.002)
Commuting Time $\times$ Female	0.019*** (0.002)	0.026*** (0.002)	0.028*** (0.002)	0.023*** (0.002)	0.025*** (0.003)
Effect of Commuting - Female	0.044***	0.042***	0.035***	0.021***	0.009***

¹ *p<0.1; **p<0.05; ***p<0.01

² Data Source: ACS 2012-2017; 68 cities.

³ The first row displays the estimated results for the quantile regression model that has the same specification as Model 4 in the base regression; the second and the third rows come from the model that has the interaction term. The last row equals the sum of rows 2 and 3.

⁴ The full model estimates are available in Appendix F.

The estimates of my first set of quantile regressions are illustrated in the first row of Table 1.5. The results revealed a monotonically decreasing relationship between commuting premiums ($\beta_{1,\tau}$ in Equation 1.3.2.1) and wages by quantile. For individuals belonging to the 10th percentile of the wage distribution, about 3% wage increase is associated with commuting one more hour. However, the correlation coefficient decreases to 2.7% when I look at individuals in the first quartile. People situated at the median of the income distribution gain about 2% of wage increase by commuting, and the number further decreases to only 0.9% at the 75th percentile, though the coefficient is still significantly positive. When I look at high-income individuals at the 90th percentile of the distribution, I notice the association of commuting time flipped in sign. Namely, individuals in the 90th percentile tend to have a lower wage, about 0.5%, when they commute one more hour. Therefore, the main driving force of the positive correlation I observed in my previous analysis comes from the left end of the wage distribution, suggesting that workers with lower-paying jobs are being compensated more for commuting.

Similar to what I did in Section 1.5.1, I allow men and women to have different com-

muting returns in the second specification and present the results in the lower panel of Table 1.5. The estimates showed that the monotonically decreasing trend stays the same for both male and female workers. However, the female commuter premium, $\beta_{3,\tau}$ in Equation 1.3.2.2, stays relatively constant. It increases in lower quantiles, starting from 1.9% in the 10th percentile to 2.8% in the median of the distribution. After the median, the coefficient remains relatively stable across the higher end of the distribution. These results suggest that while male workers keep getting lower and lower commuting compensations as I move toward high-income individuals,¹⁸ women’s additional commuting remuneration level, compared to men, is relatively income-distribution-independent.

The decreasing commuting return across the distribution clearly demonstrates the diverse compensation effects between high and low-income groups. One possible explanation for this is the spatial sorting pattern within the cities. For example, using the U.S. Census information, Couture, Gaubert, Handbury, and Hurst (2020) has shown that city downtown areas, where presumably all jobs are located, have been attracting more rich households and fewer poor ones. This also indicates the possibility that richer households can afford to live closer to where they work compared to poor ones, who tend to live at the periphery of the city and suffer from long-distance commutes. In Table 1.6, I compare the commuting mode distribution between individuals belonging to the top 25% and the bottom 25% income group in the study sample. Among the top 25% income earners, 83.4% go to work using private vehicles. In contrast, 92.76% of the bottom 25% income earners commute by car, about 10% more than the other group. Moreover, about 8% of the top quarter group travel by public transportation like buses or subways, while only 3.5% of the bottom quarter do the same. This evidence supports the idea that high-income individuals tend to live closer to downtown or Central Business Districts where public transportation systems are more developed, and low-income ones tend to live further away and commuting through private cars is more plausible.¹⁹ Notice that the commuting mode differences could lead to a higher commuting cost for low-income groups due to the additional spending associated with private vehicles, such as fuel, maintenance, insurance, and parking. In contrast, public transportation tends to be more cost-effective for commuters because the costs are spread out over a larger group of people, and the fares are typically low. This could partially explain the higher commuting-wage correlation among lower-income individuals. Furthermore, the differences in commuting modes could also alter the dis-utility different income groups need to bear. For example, for the low-income group that cannot afford to use private cars, going to work by public transportation could be much more unpleasant compared to high-income groups due to barriers such as lack of access. Poorer and remote neighbourhoods and communities often have limited access to public transportation, making it more difficult for residents to get to work. This scenario can also result in longer commuting times or the need to transfer between multiple modes of transportation, which can be inconvenient and time-consuming. Therefore, low-income commuters may require increased commuting compensations.

Another potential reason stems from the different job characteristics. For instance,

¹⁸Similar to what I discovered with the first quantile regression, male workers are being punished for commuting when they are at the right end of the distribution.

¹⁹Unfortunately, I do not have residence-workplace distance information in this data.

Table 1.6: Commuting Mode: the Bottom and the Top 25% Income Earners

<i>Commuting Mode (%)</i>	Bottom 25%	Top 25%
Private Vehicles (including motorcycles)	92.76	83.4
Public Transportation	3.49	7.97
Biking/Walking	1.23	1.4
Others	0.58	0.53
Work From Home	1.95	6.69

¹ Data Source: ACS 2012-2017; 68 cities.

high-income workers are often in positions that allow greater flexibility,²⁰ enabling them to adjust their schedules to avoid congestion or to decide when, or even if, they commute. The literature supports this view: Bick et al. (2020) found that highly educated, high-income individuals are more likely to hold jobs that can be completed remotely. Conversely, lower-paid jobs, as documented by Ecke, Magdolen, Chlond, and Vortisch (2022), typically lack this privilege; most workers in these roles cannot work from home and do not have flexible schedules, reinforcing the divide in commuting experiences based on income. My evidence in Table 1.6 supports this opinion, where I revealed that the proportion of people working from home in the top 25% is more than three times that of the proportion in the bottom quarter. This means that the commuting cost is effectively reduced to zero for those who work from home, and the scenario is much more likely to happen for high-income individuals, lowering the average commuting cost for that group. In Chapter 3, I further explore this aspect of workplace commuting and investigate how different job flexibilities impact workers' commuting costs, wages and the city structure.

In addition to the compensation disparities across the income distribution, it is also interesting that the commuting return gender gap primarily stays the same for women. It indicates that, compared to men, women are being compensated more no matter their position in the income distribution. These results could signal women's fundamental additional compensation needs when it comes to commuting, which could be the results of women's preferences towards more flexible and closer jobs (Chen & Luo, 2022), their intermediate activities while commuting such as childcare (Ignacio, Molina, & Velilla, 2022; Shuman et al., 2022), females' higher disliking for commuting (Jacob, Munford, Rice, & Roberts, 2019; Hu, Sobhani, & Ettema, 2023) or the residential location choices which tend to centre around their male partners (Escamilla Guerrero, Lepistö, & Minns, 2022). In Chapter 2, I will examine females' higher commuting returns using the instrumental variables approach and discuss all these potential explanations in more detail.

²⁰The term *flexibility* is defined here as the ability to perform work remotely (at least partially) or to choose working hours, even if the total hours tend to be fixed for full-time roles.

1.6 Conclusion

My paper aims to further our understanding of the connection between wage and commuting time. First, I established a significant positive correlation between commuting and wages by performing regressions with various control variables and isolating the role of commuting from the other factors. Through several mean and quantile regressions, I draw three main results. First, there exists a non-negligible gender difference in the correlation between commuting times and wages. When disaggregated by gender, I found that the positive return is mainly driven by women, while the coefficient for males is small and insignificant. Second, when applying quantile regression techniques, I discovered that the additional commuting returns received by female, relative to male, largely stays the same across the income distribution. These findings suggest that the commuting gender gap is significant and income-independent, signalling a more fundamental compensation demand from women. Last but not the least, I discovered a monotonically decreasing relationship between the commuting coefficient and the quantile of interest. Namely, higher-income male workers tend to have lower (sometimes negative) commuting returns.

These results emphasize the significance of heterogeneous commuting effects channelled through gender and income distribution. In Sections 1.5.1 and 1.5.2, I discussed some potential explanations. For example, commuting might be harder for female workers working in city-centre-concentrated industries. In addition, the greater family responsibilities women typically bear within their households should not be ignored.

Moreover, the fact that commuting return is lower for higher-income individuals may indicate the systematic differences between different types of jobs. Several theories discussed in Section 1.5.2 help explain this pattern. For instance, spatial sorting within cities may result in shorter commutes for wealthier households, reducing their commuting costs. Additionally, high-skilled, high-income workers often occupy jobs that can be performed remotely or have the authority to choose their working hours. In summary, while commuting does not require compensation for higher-income male workers, it must be offset by higher wages for lower-income individuals. My findings challenge the conventional theory of compensating differentials and commuting returns, where a positive relationship between commuting time and wages is often assumed. At the very least, my analysis proves that the “compensating” effects of commuting are far from robust. Any correlation found can be misleading if the heterogeneous effects across gender and income distribution are not adequately addressed.

One drawback of this study is that I cannot make any causal inference based on my regression estimates due to the endogeneity of commuting times. People’s location of residence is unlikely to be exogenous. Namely, most people self-select to live in the place of their residence, and any commuting costs are likely taken into account when they make the decision. The scenario creates a typical self-selection bias, where some unobserved but nonrandom factor is involved with the manifestation of my observations (Clougherty, Duso, & Muck, 2016). As a result, any estimates presented in this Chapter can only be viewed as correlation, not causation. In Chapter 2, I address the endogeneity problem of commuting time and take a closer look at the causal relationship between commuting times and wages.

Chapter 2

Addressing the Endogeneity of Commuting Time

This chapter considers the differential impact of commuting time on wage disparities between genders in urban contexts, when addressing the endogeneity of commuting times. Using data from the 2016 American Community Survey (ACS), I construct several instrumental variables (IV) that exploit exogenous characteristics of city shape and network connectivity to attempt to isolate the effect of commuting on wages, providing insights into the potential causal relationship. This approach mitigates the potential issues associated with residential and work location choices. My analysis reveals that the gender difference in commuting premium is primarily driven by marital status, with married women and single men requiring higher wages to commute. This study connects to research on wage-commute trade-offs and the causal impact of commuting time on various socio-economic outcomes.

2.1 Introduction

In this paper, I examine the influence of commuting times on the gender wage gap in urban areas. My analysis takes into account the potential endogeneity problem of commuting times due to unobserved heterogeneity (for example, geographic sorting). In particular, I employ an instrumental variable (IV) approach, using two exogenous characteristics inherent to a city: its geographical shape and network connectivity. The shape of a city is a good predictor of commuting time as it is largely based on geography and less obviously affect wages. In addition, city shapes as determined by geographical landscape are not prone to rapid changes. Network connectivity, referring to the infrastructure and transportation systems in place within a city, are also likely determinants of commuting times, but unlikely to distinctively affect individual wages. My objective is to use these exogenous factors as instruments to tease out the causal effects of commuting times on the observed wage gap, providing a fresh perspective to the literature on gender wage disparities.

The persistence of the gender wage gap in the labour market, even after accounting for

traditional human capital variables, has been an ongoing concern and provides the motivation for this research (Blau & Kahn, 2008, 2017). Many past studies that try to explain this persistent gap tend to focus on family-responsibility-related aspects. For example, see Bertrand, Goldin, and Katz (2010), Goldin (2014), Adda, Dustmann, and Stevens (2017), Kleven, Landais, Posch, Steinhauer, and Zweimuller (2019) and Kleven, Landais, and Søgaaard (2019). Despite significant progress over the years, this inequality remains unresolved, spurring my exploration into less examined factors that might contribute to the discrepancy. One of these potential factors, often overlooked in mainstream research, is the role of commuting times. Commuting is an unavoidable part of the daily routine for most individuals working at fixed locations. In the labour market, particularly in urban areas, differences in commuting behaviours between genders are pronounced. For instance, women are observed to have more localized commutes compared to men, especially in urban areas (Wyly, 1998). This observation has remained stubbornly persistent, even in the face of increasing female participation in the economy (Crane, 2007). Moreover, studies have shown that women in different-sex couples tend to have shorter commuting times compared to those in same-sex couples, while men generally have longer commutes (Oreffice & Sansone, 2022).¹ These trends suggest a potential correlation between commuting times and the gender wage gap, and therefore, the need for an in-depth investigation. I delve into how commuting times could influence wage disparities, focusing on urban areas where such differences in commuting times are more evident. This focus is significant not only for providing a new perspective in understanding the wage gap but also for informing public policies aimed at reducing wage inequality. The insights derived from this research can guide more effective interventions, for instance, in public transportation planning or flexible work arrangement policies, with the potential to narrow the persistent wage gap.

Addressing endogeneity of commuting times proves to be a primary challenge when analyzing the impact of commuting times on wages due to the intricacies of residential and work choices. The phenomenon of geographic sorting, where individuals tend to select cities with higher wages and more extensive job opportunities, increases population density and subsequently commuting times. For example, Moretti (2012) find that high-skilled individuals often gravitate toward larger cities seeking higher wages and broader job opportunities. Additionally, Costa and Kahn (2000) also argue that skilled couples, especially two-earner households, tend to choose to live in large cities to better deal with the working location issues. Such decisions obscure the direct impact of commuting on wages, potentially skewing results obtained through conventional methods like Ordinary Least Squares (OLS) analysis towards biased and inconsistent outcomes.² This oversight in adequately addressing commuting time’s endogeneity has made difficult our understanding of its role in wage disparities, particularly in gender wage gap discourse.

My study seeks to bridge this gap and address the challenges posed by the endogeneity of residential and workplace choices. By focusing on homeowners rather than renters, I mitigate biases arising from the flexibility of renters’ residential decisions, which are often closely aligned with their work locations. I also construct several instrumental variables

¹Also see Kwon and Akar (2021), Lee, Lahr, and Wang (2022), Campaña and Gimenez-Nadal (2022) and Bajracharya, Shrestha, and Bhatta (2022).

²I provide more detailed explanations on the endogeneity issue of commuting times in Section 2.3.

(IV) that exploit two exogenous characteristics of a city: its shape and the connectivity of its transportation network, predicated on the assumption that while these factors influence commuting costs, they remain uncorrelated with individual wage levels.

The analysis acknowledges potential concerns that the historical evolution of employer locations could impact the wage-commuting correlation. In this regard, I focus on data from a singular year (2016) from the American Community Survey (ACS) and abstract from the dynamics of employer location.

This paper is closely related to multiple lines of research. First, I focus on commuting times as a plausible determinant of the unexplained gender wage gap.³ Apart from family responsibilities, mainstream studies on this topic also claim that gender discrimination is the primary cause of the persistent gap. For example, Gibelman (2003) use the 1998 Bureau of Labor Statistics data and confirms persistent salary gaps in human service sectors due to ongoing discrimination.⁴⁵ Some recent literature also emphasizes the critical role of compensating differential. Specifically, women seem more willing to bear wage penalties in exchange for job amenities such as flexibility and low job pressure (Goldin, 2014; Blau & Kahn, 2017). While these established lines of research emphasize various aspects of the gender wage gap, my study introduces commuting as a significant, yet often overlooked, component intertwined with these factors. Commuting serves as a bridge between the compensating differentials and the inherent preferences and constraints faced by workers. On one hand, travel time is a pivotal job attribute affecting workers' decisions and the compensation they require. On the other hand, factors influencing travel times such as family responsibilities⁶ can elucidate the differential preferences men and women may have towards commuting duration. As I mentioned in Chapter 1, assuming commuting time is known *ex-ante*, then the decision to accept a job offer inherently includes a choice regarding the length of the commute. Consequently, differences in commuting time between genders are likely to play a role in explaining at least part of the gender pay gap. However, while the gender wage gap has been a focal point of numerous studies, the specific link between commuting time and this wage disparity remains largely unexplored. One exception is Arntz, Yahmed, and Berlingieri (2022), who present an interesting study using panel data from Germany and finds that working from home is associated with lower wage gaps among parents, but only fathers seem to enjoy a pay increase after transitioning to remote work. While this paper focuses specifically on the working-from-home mechanism, I have incorporated that as part of a broader definition of *commuting*.⁷ To the best of my knowledge, this paper is the first to explore the possible causal role that commuting time

³See, for example, Nishihara (2022).

⁴Also see Madden (1973), Darity and Mason (1998) and Lips (2013).

⁵Others have highlighted other factors that could influence the wage disparities between men and women, including lifetime working experiences (Drolet, 2002), differences in employment (Olivetti & Petrongolo, 2008; Dynan, Kirkegaard, & Stansbury, 2022), unequal opportunity (Yu & Liu, 2022), productivity (L. Ma & Ye, n.d.) and occupational segregation (Petersen & Morgan, 1995; Darity & Mason, 1998; Anker, 1998; Charles & Grusky, 2005; Lonzona Jr, 2022).

⁶Albanese, Nieto Castro, and Tatsiramos (2022) has indeed shown that 75% of the first-born child penalty is due to gender disparities in non-local employment and that mothers are more likely to give up on their non-local jobs.

⁷In my sample, for example, observations that worked from home have a commuting time of zero.

may play in shaping gender wage gaps.

Second, my article aligns with the literature on wage-commute trade-offs, a topic of enduring interest in academic circles. For example, Dauth and Haller (2020) use administrative data from Germany to analyze how job changers weigh commuting distances against wages. Contradicting the concept of loss aversion found in earlier studies, they found that some workers prioritize shorter commutes and are willing to accept lower wages, underscoring the significant personal costs of commuting. Jost (2024) examines the commuting behaviours of German workers through geo-referenced data, highlighting how past commuting experiences shape current decisions and the significant positive effect wages have on commuting times. This paper focuses on gender and commuting. Men and women, influenced by diverse societal roles and expectations, might value commuting times differently, potentially leading to distinct wage outcomes. This question has been examined using structural models that focus on the willingness to pay for commuting.⁸ Perhaps the paper that aligns most closely with ours within this literature is Manning (2003), which utilizes cross-sectional data from the United Kingdom to ascertain that commuting exerts a greater influence on women’s wages compared to men’s. More recently, Liu and Su (2020) and Le Barbanchon et al. (2021) address specifically differences in willingness to pay for commuting by women using a job search model where commuting matters.

Last but not least, my paper relates to the literature examining the causal impact of commuting times. The literature has investigated, through various empirical techniques, how commuting time affects urban sprawl (Travisi et al., 2010; Zhu, Zhao, & Jiang, 2022); life satisfaction and stress level (Beño, 2022; Carpentier-Postel, Gerber, Guyon, & Klein, 2022; Jin et al., 2022; Maheshwari, Van Acker, De Vos, & Witlox, 2022; Wu, Sun, Yun, Xiao, & Zhu, 2022; Erdoğan & Watson, n.d.; Asongu & Salahodjaev, 2022); school performance (Tigre et al., 2017; Jamil et al., 2022); family conflict (Laß & Wooden, 2022); labour productivity (Gimenez-Nadal & Molina, 2011; Demiral, 2018; Farré et al., 2020) and consumption (Huang, Zhan, Huang, & Wu, 2022). This paper tackles the potential causal impact of commuting time on wages, a topic with limited empirical exploration to date. I use the two-stage least square with multiple instrumental variables that exploit the exogenous variation in city shapes and network connectivities. My most promising instrument is closely related to Farré et al. (2020), who also use the shape of cities to instrument commuting and estimate its causal effect on labour force participation.⁹ However, my paper differs from Farré et al. (2020) on two grounds. First, the focus of the analysis is wage rather than participation. Second, I measure commuting time individually, while Farré et al. (2020) aggregate on the city level based on the commuting time among white males. My approach increases the variation in commuting patterns to potentially increase our understanding of its effects on wages.

Incorporating the instrumental variable approach, which capitalizes on the distinct characteristics of city shape and network connectivity, I unveil fresh insights into the gender

⁸See Van den Berg and Gorter (1997), J. Van Ommeren, Van den Berg, and Gorter (2000), Guglielminetti, Lalive, Ruh, and Wasmer (2015), Caldwell and Danieli (2020) and Nagler, Rincke, and Winkler

⁹Papers such as Albanese et al. (2022) also investigate the relationship between commuting and labour market participation differences between male and female.

wage gap. While the network connectivity instruments turn out to be weak, the instrument focusing on city shape provides promising empirical evidence. Central to my findings is the pronounced influence of marital status on the gendered commuting premium. Specifically, both married women and single men tend to seek higher wages in exchange for lengthier commutes. Such distinctions underscore the intricate interplay between commuting times, gender, and wages. These revelations not only spotlight the multifaceted nature of the gender wage gap but also underscore the need to consider a broader range of factors, such as commuting times, in our attempts to understand and address wage inequalities.

The structure of this chapter is as follows. Section 2.2 provides a detailed description of the study sample. Section 2.3 outlines the two-stage least-squares methodology, explains the process for obtaining the instrumental variable for commuting times, and offers a preliminary analysis of the instrument’s properties. Section 2.4 reports the results of my IV estimation and discusses several potential theories, while Section 2.5 concludes.

2.2 Study Sample

2.2.1 Overview

The original data come from the public version of the American Community Survey (ACS) 2016, downloaded from IPUMS USA, a website managed by the University of Minnesota and provides access to integrated samples from ACS (IPUMS USA, n.d.-b). ACS is a mandatory annual survey conducted by the U.S. Census Bureau and provides a detailed statistical portrait of the U.S. population (U.S. Census Bureau, 2018b).¹⁰ Topics of ACS include educational attainment, income, migration, and employment (U.S. Census Bureau, 2018c, 2019b).

My study sample includes homeowners between the ages of 25 and 60, employed and are either married or never married. I exclude separated and divorced people due to the potential complexities of their financial situations.

Similar to my approach in Chapter 1, due to the lack of job tenure information in the U.S. data, I select employees who work at least 30 hours per week and at least 50 weeks within a year and convert the reported annual wage income in ACS to hourly rate.¹¹ I acknowledge that this approach could result in over-estimated hourly wages in some observations if the person worked more than 50 weeks in 2016. I eliminate those working at less than the minimum wage based on the estimated hourly wage rates.¹²

I also restrict my study sample to observations working in identifiable metropolitan areas based on the 2013 definitions for metropolitan statistical areas (MSAs) from the U.S.

¹⁰Over 3.5 million households across the country are contacted every year to participate in the ACS (U.S. Census Bureau, 2019b).

¹¹I divide the reported amount by the product of working hours per week and 50, assuming that most full-time workers work 50 weeks every year and enjoy at least 2 weeks of vacation.

¹²The federal minimum wage in 2016 was \$7.25/hour, and I set the lowest estimated wage in my sample to be \$7.5. No individuals with the highest wages were excluded from my analysis.

Office of Management and Budget (IPUMS USA, n.d.-c) and having less than three hours of round-trip commuting time. People who are self-employed or working in the armed forces are also excluded.

To ensure the credibility of my results, I again follow the same procedure as in Chapter 1 and exploit each occupation’s task requirements. Each occupation is measured on five dimensions related to routinize: non-routine analytical; non-routine interactive; non-routine manual; routine-manual, and routine-cognitive. This approach to measuring occupational tasks was initially introduced by D. H. Autor et al. (2003) and has become a widely accepted method for more accurately controlling for occupational differences. Following a similar methodology to Warman and Worswick (2015), I align the SOC codes in my data with the detailed skill requirement scales provided by the Occupational Information Network (O*NET).¹³ The relevant job characteristics are divided based on the five task groups. For example, the non-routine analytical group contains variables such as innovation, critical thinking, active learning and complex problem solving; while the routine manual tasks include variables like finger dexterity and wrist-finger speed.¹⁴ A Principal Component Analysis (PCA) is then executed to reduce the dimension of the data to 5. I also weigh the PCA using the occupational distribution in the original data. The estimated loading factors are then used to calculate the indices of each of the five groups for a given occupation, which in turn serve as the occupational controls in my regressions.

2.2.2 Summary Statistics

My final study sample contains 315,759 observations. Refer to Appendix C for the description of the variables. Table 2.1 presents the weighted summary statistics for the study sample. The mean commuting time is 0.92 hours or about 55 minutes. Most of the observations are Caucasians and have at least associate degrees. Moreover, about 80% of the study sample are married people.

2.3 Methodology

One of the drawbacks of my OLS estimation in Chapter 1 is that I did not consider the endogeneity of commuting times. In particular, it is likely that there exists omitted variable bias in my OLS model, which can have a significant impact on the estimates and interpretation of OLS regression models.

Omitted variable bias occurs when a relevant variable is left out of the model, either due to unobserved heterogeneity, data availability, or lack of awareness. When this happens, the estimated coefficients of the remaining variables may be biased and inconsistent, as

¹³The O*NET database contains standardized and occupation-specific information on the tasks required for a given occupation, through which I can infer the occupational task indices. The SOC to O*NET reference comes from <https://www.onetcenter.org/taxonomy.html>

¹⁴Detailed characteristic descriptions can be found in Appendix B.

Table 2.1: Summary Statistics

<i>Continuous Variables</i>				
	Min.	Median	Max.	Mean
Log Estimated Hourly Wage	2.02	3.31	5.96	3.31
Commuting Time	0	0.83	3	0.92
Age	25	45	60	43.21
<i>Discrete Variables (%)</i>				
Gender	Female: 42.97			
Marital Status	Single: 22.68			
Race	Caucasian: 75.33		African-American: 9.23	
Education	High School: 16.53		Associate: 30.8	
	Bachelor: 29.11		Graduate: 18.44	

Data Source: ACS 2016

they fail to capture the relationship between the dependent variable and the omitted variable. This type of bias can lead to incorrect conclusions about the direction, magnitude, and significance of the relationship between the dependent variable and the independent variables in the model. In the case of commuting times and wages, the primary source of omitted variable bias is unobserved heterogeneity. Unobserved heterogeneity refers to the presence of unmeasured factors that affect both commuting time and wages. One example is access to local transportation amenities such as public transportation and shared bike services. Access to these services will affect commuting, but these typically also increase the cost of housing. Hence the presence of local transportation amenities might be associated with both higher wages and shorter commuting. Another example is that individuals who have a higher tolerance for commuting may also have personality traits or preferences that make them more successful in their careers, leading to higher wages.

The existence of this type of bias means I have legitimate concerns that my independent variable (commuting time) is endogenous, meaning that it is correlated with the error term in the regression model. To address potential biases and enhance the validity of my estimates, I adopt an instrumental variable (IV) estimation approach using a two-stage least squares method, which will be explained in more detail in the next section. The instrumental variable helps produce estimates that are less affected by endogeneity, providing a clearer understanding of the relationship between commuting time and wages.

2.3.1 Two-Stage Least Squares

The two-stage least squares (2SLS) regression analysis is a statistical technique employed when the error terms of the dependent variable correlate with the independent variables. This correlation can lead to omitted variable bias and inconsistent Ordinary Least Squares (OLS) estimates. The instrumental variable is used to isolate the variation in the independent variable that is exogenous to the error term, and thus estimate the causal effect of the independent variable on the dependent variable. Conceptually speaking, I aim to “separate out” the portion of the commuting time that remains exogenous to the error terms.

The first-stage and second-stage equations can be represented as follows:

$$CT_{i,c,s} = \alpha_0 + \alpha_1 IV_c + \alpha_2 State_s + \omega^\top x_i + u_{i,c,s}$$

$$\log(Wage_{i,c,s}) = \beta_0 + \beta_1 \widehat{CT_{i,c,s}} + \beta_2 State_s + \gamma^\top x_i + \epsilon_{i,c,s}$$

Here, CT symbolizes the two-way commuting time in hours, $State$ controls for the state, and x_i comprises individual control variables such as age, age squared, industry, race, education levels, number of children (excluded from the single male and single female sub-samples), the criterion of having all children under 14 (also not applicable to single males and single females sub-samples), and the five occupational skill indices: non-routing analytical, non-routine interactive, non-routine manual, routine manual and routine cognitive. By replacing the original commuting time with the estimated exogenous component, I satisfy the exogeneity assumption of OLS in the second equation. Conceptually, this means I filter out any endogenous influences from my key predictor, allowing me to estimate its causal effect better.

In practice, IV analysis requires careful selection of an appropriate instrumental variable. In particular, I will need to identify an instrument variable that is correlated with the independent variable of interest, but is not correlated with the error term or any other omitted variables in the regression model. In other words, my instrument needs to satisfy the following two properties:

1. **relevance:** the instrument is correlated with commuting times; that is, $corr(IV, CT) \neq 0$.
2. **exogeneity:** the instrument is uncorrelated with the error terms of the model; that is, $E(\epsilon|IV) = 0$.

If those conditions are met, then by regressing commuting time on the instrument (and other exogenous regressors) I will be able to obtain the exogenous part of commuting time and use that as my dependent variable of interest in the second stage. In other words, the $\widehat{CT}_i$ will only contain the exogenous component of commuting times, while the endogenous part has been filtered out by the instrument in the first stage regression.

In this study, I test three instruments separately:

1. the normalized cohesion index;

2. the average node degree;
3. the proportion of self-loop segments.

In the following sections, I will explain each instrument in detail, document how they are constructed, and discuss why I believe they satisfy the relevance and exogeneity conditions.

2.3.2 Normalized Cohesion Index

The cohesion index measures the compactness of a city. Namely, how close the shape of a city is to a circle. I follow Farré et al. (2020) and Harari (2020) and treat the shape of cities as exogenous sources of variation for travel times. Compactness is likely determined by the geographical characteristics surrounding a city, such as the presence of natural barriers or features that influence urban growth patterns. For example, mountains or water bodies like lakes, rivers, or oceans can limit the spatial expansion of a city in specific directions. As stated in Cervero (2001), the shape of cities significantly influence intra-urban commuting costs, and if a city is more compact in its shape, individuals living in the city tend to enjoy shorter commuting times. In particular, if a city is more geometrically compact, then it is easier to form an effective transportation system within-city, resulting in shorter commuting trips. Therefore, the relevance assumption is satisfied.

One main concern to this identification strategy is that cities with no geometric limitations might be more developed, bigger in size, and offer on average higher wages to their workers, which will violate the exogeneity condition. To take into account this concern, I follow Farré et al. (2020) and normalize the cohesion index so that it is uncorrelated with city size. This would mean that my instrument will only reflect the geometric restraints, which I believe are exogenous. The city might expand over time, but the geographical constraints largely remain the same and thus influence the city’s shape in the same manner throughout time. Hence, it is unlikely that the city will grow significantly “out-of-shape” due to endogenous expansion. By comparing the GIS file downloaded from NHGIS, I have verified that between the years 2013-2016, all of the cities in my study sample have remained the same in their shapes and estimated normalized cohesion, supporting my claim that, at least in the short term, the shape of the city is unlikely to change and violates the exogenous condition.

To obtain the normalized cohesion index, for each metropolitan area, I first overlay a square grid of size 4000 by 4000¹⁵ to the shape of the area and compute its cohesion index as follows:¹⁶

I first calculate the cohesion index for each city, which is equal to the average distance

¹⁵Due to computational limitations, this is the finest grid I can reasonably apply.

¹⁶Farré et al. (2020) also introduced proximity instrument, but the instrument was proven to behave very similar to cohesion indices. Furthermore, the proximity index utilizes a fundamental assumption that all trips are towards the city centre, which is unlikely to be true as multiple studies have challenged the monocentric city structure assumption (see Papageorgiou and Pines (1999), for example).

between all pairs of grid points within a city:

$$Cohesion_c = \sum_i^N \frac{d_{ij}}{N(N-1)} \quad \forall i \neq j,$$

where d_{ij} is the distance between the centroids for grid cells i and j . Implicitly, I have assumed that the job locations and residents are sufficiently equally distributed across the city. I then calculate the same cohesion index for the area's Equivalent Area Circle (EAC). Namely, I look at what the cohesion index would be for a perfect circle-shaped city with the same geographical size as my city of interest. According to Burgstaller and Pillichshammer (2009), the cohesion index for an EAC of city c can be calculated using the following formula:

$$Cohesion_{EAC,c} = 0.9054 \times \sqrt{\frac{Area_c}{\pi}}$$

To obtain the relative compactness of the city, I then take the ratio between the cohesion index of a city's EAC and the city's actuarial cohesion to obtain the normalized cohesion index:

$$NCoh_c = \frac{Cohesion_{EAC,c}}{Cohesion_c}$$

Note that $NCoh$ will range between 0 and 1, as the $Cohesion_{EAC,c}$ will always be less than or equal to $Cohesion_c$. Moreover, the more circle-like city c is, the smaller $Cohesion_c$ is, the bigger $NCoh_c$ will be.

Note that if two cities are different in size but similar in shape, they will share a similar normalized cohesion index. A quick examination of the data reveals that the correlation coefficient between the city size and my normalized cohesion index is only about 0.14, which is fairly small and supports my claim that this instrument is not correlated with the city size. Moreover, there also exists a strong empirical relationship between city size and population. Typically, larger cities are also more populated due to their more developed infrastructure and services and better economic opportunities, which allow them to attract and accommodate larger populations (Glaeser, 2014; J. K. Brueckner, 2007; Rosenthal & Strange, 2004). By constructing an index that is independent of both city size and population, I am ensuring that the IV is only capturing the effect of city shapes/compactness on commute time.

2.3.3 Average Node Degree

Adopting concepts from graph theory and modelling the network of a city as a graph has become increasingly popular in the literature of urban planning (Barrington-Leigh & Millard-Ball, 2020; Boeing, 2019b). A graph is a mathematical model of a network and is defined to be a set containing two sets as its members: a set of nodes and a set of edges (Newman, 2003; Gastner & Newman, 2006). In graph theory, edges are best thought of as a collection of pairs of nodes, where the two members of the pair are the nodes involved in the focal relationship (Lizardo & Jilbert, 2020). In other words, an edge either connects one

node to another, or one node to itself in the case of self-loops (Boeing, 2019a). The average node degree, as a mathematical property of any graph, is simply the average number of edges per node in the graph:

$$AND_G = \frac{N_{edges,G}}{N_{nodes,G}}$$

where G is the graph of interest. Figure 2.1 illustrates a simple network with three nodes and two edges. In this particular case, the average node degree is $\frac{2}{3}$.

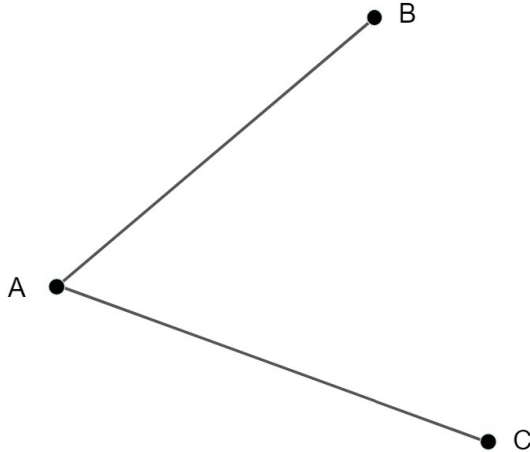


Figure 2.1: A Simple Network Illustration

In the primal representation of a city network, I view the nodes as intersections and dead ends, while the edges represent the street segments that link them (Boeing, 2019a; Porta, Crucitti, & Latora, 2006). The average node degree measures how many streets are connected to an intersection on average within the city network and is an indicator of the network’s connectivity. Intuitively, the more connected a city’s network is, the better the street network provides direct routes between locations, and the easier it is for individuals to travel from one point to another. Therefore, the relevance condition should be satisfied. Moreover, by its very definition, an average distributes the total degree over all nodes, making it more a measure of the general connectivity pattern rather than a direct reflection of the city’s size or density. As such, the average node degree operates largely independently of the sheer volume or density of a city, thereby satisfying the exogeneity condition.

To obtain the average node degree for cities, I use OSMnx, an open-sourced Python-based toolkit, to automatically download spatial data from OpenStreetMap and construct graph-theoretic objects for network analysis (Boeing, 2017, 2019b). In particular, for each network, I download all (non-private) OpenStreetMap streets and paths, and the software automatically converts the information into a graph object, from which numerous mathematical characteristics are calculated including the graph’s average node degree (Boeing, 2022). Figure 2.2 provides a demonstration of the object downloaded by OSMnx. The figure maps out the street network spanning a 900-meter radius around The White House in Washington, D.C. Within this portrayal, nodes, symbolizing intersections or endpoints

of roads, are uniquely identified based on OpenStreetMap’s conventions. These nodes are interconnected by edges, which represent the various streets or pathways. The resulting network mirrors the dense, grid-like organization that is emblematic of Washington, D.C.’s urban landscapes. With a total of 3,416 nodes and 10,273 edges, the structure has an average node degree of roughly 6.01. This indicates that, for this particular network, around six streets or paths are connected to an intersection on average.

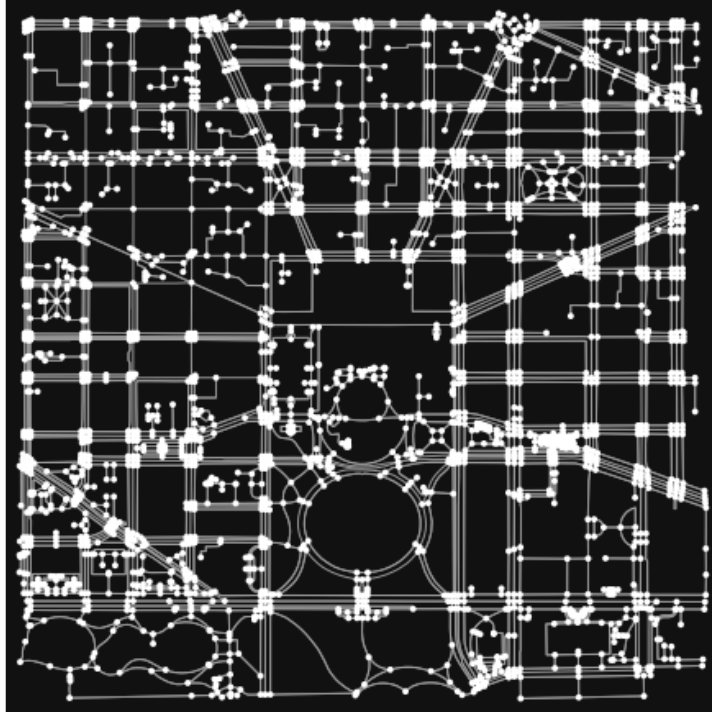


Figure 2.2: Street network surrounding The White House (900 meters radius)

2.3.4 Self-Loop Proportion

Similar to the average node degree, the self-loop proportion is another graph-theoretic statistic that is automatically generated by OSMnx. A self-loop is defined as an edge from node u to node v where $u == v$ (Boeing, 2022). In other words, street segments connect to themselves and create loops or circuits. The self-loop proportion, as its name indicates, calculates the proportion of edges that have one single incident node in the network (Boeing, 2019a). For Figure 2.2, the proportion of self-loops is a mere 0.0007, showcasing the rarity of such configurations in the analyzed area.

Intuitively, we can think of self-loops as roundabouts positioned at the end of a road, closed communities, or street segments that form cul-de-sacs. The presence of self-loops could be indicative of a city’s urban planning strategies and historical development patterns. Some cities with a higher proportion of self-loops might have evolved organically, with streets and neighbourhoods being built around existing geographical features or constraints, while others might have been planned with a more grid-like structure to facilitate

direct connections between different parts of the city. A higher self-loop proportion indicates that there exist more “closed loops” in the network of the city and fewer direct routes between locations, which can create barriers to efficient travel. For example, a self-loop may force drivers or pedestrians to take a longer route than necessary to reach their destination, leading to increased travel times and congestion, and reducing the overall efficiency of the street network.

I now perform some preliminary data exploration analysis on my potential IVs. By examining matrices such as summary statistics and density plots, I wish to gain insight into the underlying patterns and trends of those variables and make informed decisions about modelling and analysis.

Table 2.2 presents the summary statistics of all three potential instrumental variables mentioned above. Note that to ensure the comparability and the comprehensiveness, I also show the results for the standardized IVs.¹⁷ The coefficient of variance (CV) is displayed in the last column, which is the ratio between the standard deviation and the mean expressed as a percentage. A high CV indicates that the standard deviation is relatively large compared to the mean, suggesting that the variable has sufficient variation. From the last three rows, I can conclude that when compared to normalized cohesion (CV= 42.09) and the self-loop proportion (CV= 49.19), the average node degree variable exhibits the least variations in my sample with a CV equals 30.16. The self-loop proportion also displays the characteristics of a right-skewed distribution, with a mean of 0.23, much lower than 0.5.

Table 2.2: Summary Statistics for Instruments

	Min	Median	Max	Mean	S.D.	Coefficient ¹ of Variance
Normalized Cohesion	0.52	0.78	0.93	0.77	0.11	13.81
Average Node Degree	4.63	5.42	6.34	5.49	0.26	4.72
Self-Loop Proportion	0	0.005	0.023	0.005	0.003	49.19
Standardized NC	0	0.64	1	0.61	0.26	42.09
Standardized AND	0	0.46	1	0.50	0.15	30.16
Standardized SLP	0	0.20	1	0.23	0.11	49.19

¹ The coefficient of variance is the ratio of the standard deviation to the mean, expressed as a percentage.

² Data Source: ACS 2016.

³ To make the instruments comparable, all instruments are standardized to between 0 and 1 in the last three rows.

Figure 2.3 displays the density plots for the three instruments, and similar characteristics can be observed. In particular, while the normalized cohesion index appears to be

¹⁷The standardization is constructed as follows: $sIV = \frac{IV - \min(IV)}{\max(IV) - \min(IV)}$. The resulted variables all range between 0 and 1.

relatively evenly distributed, the average node degree variable is mostly concentrated between 5.25 and 5.6. The right skewness of the self-loop proportion variable is also evident from its density plot.

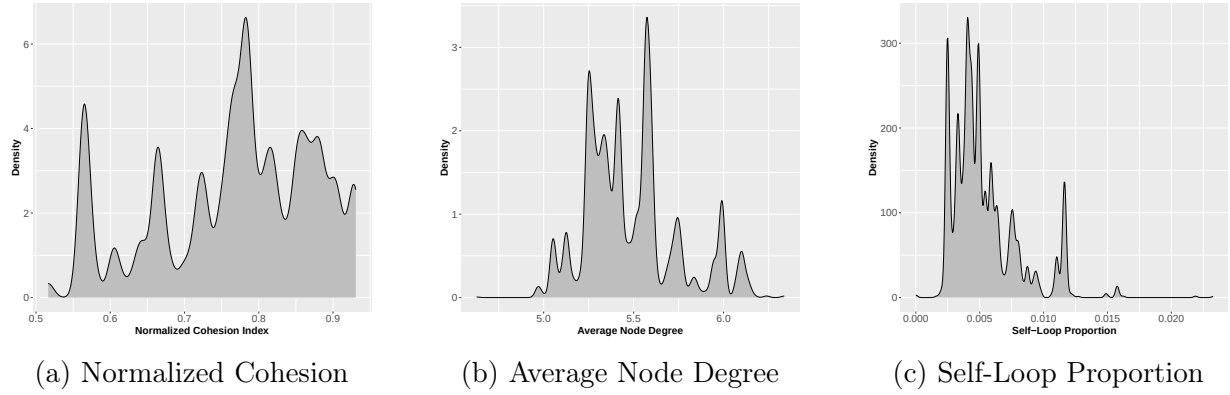


Figure 2.3: Density Plots for Potential IV Variables

2.4 IV Estimations

2.4.1 Main Results

To compare my IV estimates with the OLS estimates, I first present the results of the OLS regression in Table 2.3. In all three groups that I examined (pooled sample, married sample, and single sample), females exhibit a stronger association between commuting and wages than males. In the pooled sample, an hour of commuting time is associated with a 2.8% increase in male wages and 5.8% for females, which is more than double. The difference is even more dramatic when I look at married samples only. For married males, a 2.9% increase in wages is estimated, while that number jumps up to 6.7% for married females. The same trend is again observed for single individuals, although the scale is smaller. One more hour of commuting is only associated with a 1.8% increase in single male wages and 3.1% for single females. It appears that the higher commuting effect on wages for women is robust to marital status. In addition, married men and women have higher commuting-wage associations.

I then turn my attention to the causal effect estimations. Table 2.4 presents the IV regression results, with each panel utilizing a different instrumental variable. Panel A employs the normalized cohesion index as the instrumental variable, Panel B uses the average node degree, and Panel C applies the self-loop proportion variable. The coefficients in Table 2.4 indicate how much more wage an individual is gaining by having one more hour of commuting time. Note that my IV estimates are much higher than those estimated by the OLS regressions, which is not uncommon in the literature.¹⁸ Recall that I adopt the IV

¹⁸For example, Farré et al. (2020) uses the same normalized cohesion index to estimate the causal impact of commuting time on labour force participation rate, and the IV estimates are four times higher than

Table 2.3: OLS Results

	(1)	(2)	(3)	(4)	(5)	(6)
Commuting Effect on Wages	0.028*** (0.01)	0.058*** (0.003)	0.029*** (0.01)	0.067*** (0.004)	0.018*** (0.01)	0.031*** (0.01)
Sample	All Male	All Female	Married Male	Married Female	Single Male	Single Female
Marital Status Control	Y	Y	N	N	N	N

¹ *p<0.1; **p<0.05; ***p<0.01

² Data Source: ACS 2016.

³ All models include age, age squared, industry, race, education levels, number of children, whether all children under 14, state controls, and the five occupational skill indices.

⁴ The regression is estimated using OLS with clustered standard errors regarding working places.

⁵ Full model estimates are available in Appendix H.

analysis to address potential endogeneity in commuting times and improve the reliability of the estimates. The larger IV estimates compared to the OLS results may suggest that the OLS estimates are affected by inconsistency and potential omitted variable bias, as discussed previously.

In Section 2.3, I highlighted the primary source of omitted variable bias: unobserved heterogeneity, which can create a spurious correlation between wages and commuting times, leading to the underestimated effect in OLS regression models. To understand why, I will need to consider the potential confounding factors and mechanisms that may moderate or mediate the effects of commuting on wages. For example, workers who are willing to have longer commutes may be the ones who are new to their position and have not yet had a chance to relocate. These workers may have less experience and productivity for their position and thus lower wages. The existence of this type of commuter will decrease the overall estimates in the OLS regression. Moreover, longer commutes may lead to increased stress and fatigue and less time for leisure or family activities. These factors may also in turn decrease worker productivity and job satisfaction and increase turnover rates, which can negatively impact wages. These mechanisms are not accounted for in the OLS regression model, and therefore the estimated effect of commuting time on wages may be biased and underestimated.

Nevertheless, it is essential to point out that while the instrumental variable (IV) approach aims to identify causal effects, the commuting estimates in Table 2.4 should be interpreted with caution. Although the IV provides an attempt at isolating exogenous variation in commuting, these findings serve more as an exploratory examination of potential causal pathways rather than definitive causal estimates. Furthermore, both Panel (B) and Panel (C) exhibit low first-stage F-statistics, which tests the null hypothesis that the coefficient on the instrument equals zero in the first-stage regression. Typically, a scale

the OLS ones. Tigre et al. (2017) uses distance to the closest schools as an instrumental variable for commuting time and analyzes how commuting impact youths' school performance. Their IV estimates, although less significant, are seven times bigger than the OLS estimates in magnitude.

Table 2.4: Estimated Effects of Commuting on Wages

Panel A: Instrumental Variable - Normalized Cohesion						
	(1)	(2)	(3)	(4)	(5)	(6)
Commuting Effect on Wages	0.64*** (0.11)	0.64*** (0.1)	0.66*** (0.11)	0.74*** (0.12)	0.58*** (0.12)	0.43*** (0.09)
First-Stage F Statistic	15.16	14.91	14.17	12.07	17.78	21.85
Panel B: Instrumental Variable - Average Node Degree						
	(1)	(2)	(3)	(4)	(5)	(6)
Commuting Effect on Wages	0.4 (0.37)	0.9 (0.7)	0.45 (0.34)	0.68 (0.48)	0.35 (0.51)	-2.72 (20.56)
First-Stage F Statistic	2.16	0.58	2.32	1.12	1.37	0.02
Panel C: Instrumental Variable - Self-Loop Proportion						
	(1)	(2)	(3)	(4)	(5)	(6)
Commuting Effect on Wages	0.17 (0.3)	0.44** (0.18)	0.25 (0.27)	0.39** (0.19)	0.02 (0.29)	0.64** (0.32)
First-Stage F Statistic	1.45	2.01	1.1	2.05	4.14	1.44
Sample	All Male	All Female	Married Male	Married Female	Single Male	Single Female
Marital Status Control	Y	Y	N	N	N	N

¹ *p<0.1; **p<0.05; ***p<0.01² Data Source: ACS 2016.³ All models include age, age squared, industry, race, education levels, number of children, whether all children under 14, state controls, and the five occupational skill indices.⁴ The regression is estimated using 2SLS with clustered standard errors regarding working places.⁵ Full model estimates for the models in Panel A are available in Appendix I.

exceeding 10 is regarded as evidence of a strong instrument that is sufficiently explanatory for the independent variable. Unfortunately, my results display F-statistics below this threshold, suggesting that the employed instruments do not sufficiently explain the variation in commuting times and can lead to unreliable and inconsistent IV estimates.

For the average node degree, the weak correlation initially led me to consider the scenario commonly recognized as urban street-network sprawl.¹⁹ In cities with this kind of dense development, the increased accessibility may mask true travel times as people may switch between faster direct routes by car and slower routes by other means (Barrington-Leigh & Millard-Ball, 2020). However, controlling for people’s main travel modes in the IV regressions still yields small first-stage F-statistics. This brought my attention to the fundamental issue: a lack of variation in the IV. As illustrated in Figure 2.3 panel (b), the average node degree exhibits low dispersion and is more concentrated within a narrow range. Such low variability can be detrimental as the restricted variation diminishes my IV’s capacity to effectively capture and explain changes in commuting times.

The relationship between self-loop proportion and commuting times can be ambiguous due to the non-straightforward correlation between self-loop proportion and street network connectivity. In particular, I believe this relationship depends on the specific characteristics of the street network. In some cases, a street network with a higher self-loop proportion may actually be more connected than a network with a lower self-loop proportion. For example, in a densely built-up area where streets must navigate around buildings or other obstacles, self-loops may be necessary to create direct routes between locations. In this case, the self-loops can actually improve the network’s connectivity by providing shortcuts that would not otherwise be available. On the other hand, in a less built-up area where there are fewer obstacles, self-loops may be less necessary and may indicate that the network is less connected. For example, in a more suburban area with a grid-like street pattern, a high self-loop proportion may indicate that there are fewer direct routes between locations and that travel times may be longer. Therefore, I believe that in the context of my analysis, the evidence shows that I do not observe a strong correlation between self-loop proportion and commuting times due to the co-existence of both scenarios.

Because of the reasons mentioned above, the estimations of Panel (B) and Panel (C) may not be as informative as Panel (A), where the instrument is strong for all subgroups, and I will omit them in my following discussions and focus on Panel (A) only.

The robust higher commuting effect on wages for women is no longer present in my IV estimation. For example, in Panel A, regression (1) and (2) reveal that for both male and female workers, one more hour of commuting leads to an increase in wages of about 64%. However, by observing the coefficients with sub-groups (regression (3) to (6)), I noticed that, similar to what I observe in Table 2.3, marital status is a crucial factor impacting commuting returns significantly. For example, while both male and female commuters’ wage returns go up for the married sub-sample, the effect is more pronounced for females.

¹⁹Urban street-network sprawl typically characterizes cities with more developed networks, high population density, and comprehensive public transportation systems (Ewing & Cervero, 2010; Creutzig, Baiocchi, Bierkanndt, Pichler, & Seto, 2015). Typically, there is increased accessibility within such cities, allowing for a broader range of commuting methods including walking, bicycling, and public transportation.

Married women enjoy a 74% increase in wages by commuting one more hour, while married men only get 66%. Interestingly, in contrast to the OLS estimates, the gender trend is reversed for single persons. Namely, single males are getting higher commuting returns than single females (58% versus 43%).

2.4.2 Discussion

In this section, I focus on my findings about the diverse commuting returns, both between males and females and between married and single individuals. I provide several potential theories on what could be the driving force behind these diverse commuting premiums.

Residential Location Choice

When looking at family dynamics, it is commonly believed that women tend to be more family-orientated when deciding their residential location. In a study that exploits the married couple data in China, T. Wang, Zhang, and Zhao (2022) argues that housing provides more psychological and financial security for women than men. In addition, female decision-makers tend to buy smaller houses and have higher returns on housing assets, which could be caused by the fact that they are more concerned about the members of their nuclear family, especially their children. Escamilla Guerrero et al. (2022) uses border crossing records for French Canadian migrants from the early 20th century to study their destination choices. The study finds significant gender differences in sorting across destinations. In particular, couples' joint destinations are typically not determined by the married women's labour market opportunities but by their spouses'. As a result, married women were much less responsive to destination labour market characteristics such as job availability. As such, married women may face an increased commuting cost due to their focus on fulfilling their family members' needs. For example, they may choose to live in a location that is closer to their spouse's workplace or their children's schools, even if it means a longer commute for themselves. Additionally, married women may also have more caregiving responsibilities, such as taking care of children or elderly family members, which may require them to commute to multiple locations or make frequent stops along their route, leading to longer travel times and increased commuting costs. Overall, the prioritization of family needs and caregiving responsibilities may lead to a higher commuting cost for married women compared to other groups.

To determine if this theory fits my data, I used the spouse identifier in ACS to match husbands and wives who live in the same household. Note that I only match individuals who are already in my study sample to determine whether the theory fits my population of interest. Therefore, I am essentially looking at couples who are both in their primary working age, working full-time and in metropolitan areas. If couples' joint residential location decisions are indeed primarily determined by the husband's labour market opportunities, we can expect husbands to have higher salaries since the location decisions are based on maximizing the husband's labour market outcomes. Furthermore, wives who choose to work full-time may opt to work from home more compared to their husbands, as residential location choices may be more closely aligned with the husband's place of work.

Table 2.5 compares the means between husbands and wives regarding log hourly wage, commuting time, and the working-from-home proportion. I found that while husbands indeed have higher salaries, wives spend less time travelling to and from work, and the differences are significant. From the last row of Table 2.5, we know that the higher percentage of wives working from home can at least partially explain this observation. In other words, in my data, wives seem to have more flexible work arrangements, which could result in reduced commuting times. My observations are consistent with the theory that the location choice is primarily based on the husband’s job, and the place to live is chosen to optimize the husband’s labour market opportunities and commuting time since they are more likely to work outside of their home. Working from home allows wives to be less affected by the residential location choice, which will in turn have a smaller impact on the wives’ employment outcomes.

Table 2.5: Comparison Between Husbands and Wives

	Husbands	Wives	P-Value ⁴
Log Hourly Wage	3.44	3.25	0.00
Commuting Time ⁵	0.94	0.86	0.00
Working-From-Home Proportion ⁶	3.92	4.64	0.00

¹ Data Source: ACS 2016.

² I only match couples that are in my original study sample.

³ All estimates are weighted by person weight variable in the data.

⁴ The p-values are obtained using a two-sample t-test with corresponding weights.

⁵ Commuting time is two-way in hours.

⁶ Note that individuals that work from home have zero commuting times in my sample.

Intermediate Activities While Commuting

Intermediate activities are defined to be any additional activities that happen in between an individual journey from home to workplace or from workplace to home, and they highlight the differences in the diverse gender roles. For example, Ignacio et al. (2022) find that the majority of intermediate activities are done during the commute from the workplace to home, and the gender commuting differences are narrowed when intermediate activities are considered. Focusing more on women’s travel behaviours associated with caregiving and home-related tasks, Shuman et al. (2022) use data from the Washington Metropolitan Area Transit Authority (WMATA) and present a case study in the National Capital Region. The authors observe that, compared to men, women tend to travel more often to locations designated for caring for family members or performing household tasks, especially during weekdays. In particular, approximately 60%-65% of trips to and from daycare centers were made by women, and the trend was robustly observed at schools and grocery stores. Other studies have also found that women’s scheduling tends to be more intricate

than men’s, with females engaging in trip-chaining (journeys consisting of multiple stops or destinations) more frequently (Uteng, 2012; Vanderschuren, Phayane, & Gwynne-Evans, 2019; M. Roberts, 2016). This evidence suggests that, due to these additional intermediate activities, women tend to bear higher transportation costs compared to their male counterparts, resulting in a higher commuting premium. Moreover, because these additional intermediate activities are all strongly linked to the provision of childcare and household-related responsibilities, single women naturally bear less of this burden. This theory could be used to explain why married women have higher commuting premiums than married men. However, it does not provide answers to why single women have lower commuting premiums compared to their male counterparts.

Job Selection

Gender differences when selecting the types of occupations are non-negligible and may have a significant impact on the effects of commuting (Palffy, Lehnert, & Backes-Gellner, 2022). For example, the famous Goldin (2014) emphasizes female preferences for jobs that are more flexible so that they have more time for domestic responsibilities. Similarly, Chen and Luo (2022) investigates responses to job advertisements and finds that women, especially married ones with heavier family responsibilities, tend to avoid jobs with irregular schedules, requirements to be away for extended periods of time, and long working hours. Moreover, the paper also finds that females typically shy away from applying to jobs listing words like “competition” or “pressure” in their job posts. This seems to suggest that women tend to disproportionately avoid positions costumed to competitive pressure. Yan, Burke, and Leung (2021) noticed that female workers tend to pick jobs that are closer to home and have the shortest median commuting times. As such, apart from increased commuting opportunity costs, females may also face limited job options and might accept jobs that are not the best match for their skills and qualifications. Furthermore, female workers who prioritize job flexibility may have lower bargaining power in terms of negotiating salaries, resulting in lower wages.

Although how much pressure women experience at work is not available in my data, I do have information on the individuals’ usual working hours and the number of weeks worked. As I discussed in Section 2.2.1, I picked individuals who worked 30 hours per week and at least 50 weeks within a year to ensure an accurate estimation of their hourly wage rates. By doing so, I am also restricting my sample to men and women who are willing to work relatively long hours without extended vacation times. Under this scenario, the only channel regarding flexibility is commuting. In other words, if the job flexibility assumption is consistent with my data, then I should see lower wages and shorter commute times for women, as well as a higher working-from-home proportion among female workers. Moreover, the effects should be more prominent among married individuals. Table 2.6 compares the means between males and females in my study sample regarding log hourly wage, commuting time, and the working-from-home proportion. Panel (A) uses the full sample, and Panel (B) and (C) illustrate the results for married and single²⁰ individuals re-

²⁰The definition of “single” in my data is “never married”. I exclude individuals who are separated, divorced or widowed.

spectively. To determine whether the differences are statistically significant, I also perform the two-sample t-test and report the p-value in the last column. The results are consistent with the job selection theory. First, when looking at the pooled sample, I find that women earn significantly lower wages than men, have shorter commutes and are more likely to work from home. Second, when comparing Panel (B) to Panel (C), I find that the gender differences in wages and commuting times come entirely from the married sample, consistent with what I expected. The higher working-from-home proportion in both married and single sample seem to suggest an inherited preference for flexibility among female workers.

Table 2.6: Comparison Between Male and Female

	Male	Female	P-Value ³
Panel A: Pooled; $n = 315,759$			
Log Hourly Wage	3.39	3.20	0.00
Commuting Time ⁴	0.95	0.88	0.00
Working-From-Home Proportion ⁵	3.76	4.16	0.00
Panel B: Married; $n = 253,087$			
Log Hourly Wage	3.49	3.24	0.00
Commuting Time ⁴	0.96	0.86	0.00
Working-From-Home Proportion ⁵	4.09	4.59	0.00
Panel C: Single; $n = 62,672$			
Log Hourly Wage	3.05	3.05	0.79
Commuting Time ⁴	0.91	0.91	0.59
Working-From-Home Proportion ⁵	2.56	2.79	0.00

¹ Data Source: ACS 2016.

² All estimates are weighted by person weight variable in the data.

³ The p-values are obtained using a two-sample t-test with corresponding weights.

⁴ Commuting time is two-way in hours.

⁵ Note that individuals who work from home have zero commuting times in my sample.

In summary, compared with men, women, especially married ones, prefer jobs with more flexible hours and closer to home. My empirical evidence is consistent with this theory, and it makes sense for married women to demand more compensation when they have to spend extra time commuting to and from their workplaces.

Commuting Preferences

Differences in commuting behaviour between males and females have garnered attention in various research spheres,²¹ especially when discussing preferences related to commuting. Within the realm of labour economics, scholars have adopted structural models to better understand these preferences and their implications on wage disparity. For instance, Le Barbanchon et al. (2021) employed a structural job search model with commuting as a key variable and postulated that variations in commute valuation could explain up to 14% of the residualized gender wage gap. Similarly, Liu and Su (2020) discerned that differences in commuting preferences might explain roughly 21% of the observed gender wage discrepancy.²²

While my research does not rest on a structural model, it can be used to shed light on how commuting preferences manifest in observed wage outcomes and reveal to what extent my data supports these theorized preferences posited in structural models. Direct measurement of commuting preferences is a challenge, as such nuanced information isn't explicitly available in my dataset. Yet, there exist empirical studies that offer a window into the gendered attitudes towards commuting, providing essential context for my analysis. For example, Hu et al. (2023) found that although males were more sensitive to the road environment (for example, constructions or congestion) than women, women tend to experience more psychological stress and pressure from commuting. The more significant commuting dis-utility experienced by women could partially explain why I found married women to have higher commuting returns. However, my evidence also suggests that single women do not seem to share this type of commuting dis-utility, as they obtain less commuting compensation. Therefore, it is likely that the type of dis-utility is more prominent for women who bear more family responsibilities.

Wener, Evans, and Boately (2005) takes advantage of a natural experiment where a major infrastructure improvement took place for a commuter rail line, enabling a “one-seat ride” to New York City for numerous commuters who previously had to transfer to an additional train. The authors sought to understand how this inherently reduced commuting time affected commuting stress. One of the principal revelations from their study was that women with children at home stood as the primary beneficiaries of this infrastructure enhancement, experiencing the most significant reduction in commuting-related stress. The authors suggest that this group may be especially sensitive to commuting; thus, any improvement in the commuting experience would be particularly valuable to them. If this were broadly applicable, one might expect such women to demand a higher wage premium for longer commutes as compensation for the increased stress they endure.

²¹For example, transportation (McQuaid & Chen, 2012; Liu, Yamamoto, & Yao, 2022; Martín-Barroso, Núñez-Serrano, Turrión, & Velázquez, 2022), psychology and well-being (Dilmaghani, 2021; J. Roberts et al., 2011; Stutzer & Frey, 2008; Clark, Chatterjee, Martin, & Davis, 2020; Matthews et al., 2022; L. D. Murphy, Cobb, Rudolph, & Zacher, 2023; Hu, Sobhani, & Ettema, 2022; Tao, Petrović, & van Ham, 2022; Baek, Yoon, & Won, 2022; X. Wang et al., 2023), and urban planning (MacDonald, 1999; Crane, 2007)

²²See also Velásquez (2022), which investigates the interdependent commuting choices among dual-earner households.

Building upon the insights provided by the literature, I sought to examine my own data, focusing on marital and parental statuses. Table 2.7 displays the number of individuals in my sample by sex, marital status and whether they have children or not. I found that only a small proportion of single individuals in my sample have children (about 3%), which may limit my ability to draw meaningful conclusions about the relationship between parental status and commuting premium for this particular group. As a result, I decided to run a robustness check on the pooled sample while controlling for marital status and then exclude single individuals from my regression analysis as a sensitivity analysis. Doing so helps to ensure that my estimates are based on a more representative sample and reduces the risk of biased estimates due to the small sample size.

Table 2.7: Counts by Gender, Marital Status and Children

Gender	Marital Status	Have Children	Count ¹	Percentage ²
Male	Single	No	30,143	9.55
Male	Single	Yes	3,513	1.11
Male	Married	No	44,550	14.1
Male	Married	Yes	100,380	31.8
Female	Single	No	22,627	7.17
Female	Single	Yes	6,389	2.02
Female	Married	No	40,628	12.9
Female	Married	Yes	67,529	21.4

¹ The counts are unweighted.

² As a percentage of the total unweighted sample size.

³ Data Source: ACS 2016.

Panel A in Table 2.8 displays the results of IV estimates on the male and female, separated by whether they have children or not. I find that first, contradicting what Wener et al. (2005) found, females with children are not the only group that requires the most compensation for commuting. In fact, males with no children and females with children both have the highest estimated commuting effects in my data. Second, I find that parental status has the opposite effects on males and females regarding commuting returns. One more hour of commuting causes male wages to rise by 71% if they have no children, but only 60% for those who have children. For females, the premium rises from 56% to 71% when I look at mothers. From a preferences perspective, my analysis indicates that males with no children and females with children both dislike commuting.

This opposite preference trend and the resulting commuting premium for men and women with different parental statuses may be due to differences in societal expectations and gender roles. For example, in most societies, women are still expected to be the primary caregivers for children, and this can impact their ability and willingness to work longer hours or take jobs with longer commutes. Women with children may prioritize time with their families over commuting time and may be more likely to prefer shorter

commutes. Male workers with children, on the other hand, may see a longer commute as a necessary sacrifice in order to provide for their families. Furthermore, I suspect work-related stress might also play a role. Speculatively and from a psychological perspective, workers who dislike commuting may experience higher levels of work-related stress, which can impact their overall job satisfaction. Male workers without children may be more likely to have high-stress jobs that make a long commute even more challenging. Similarly, women with children may experience additional stress related to balancing work and family responsibilities, which can make a longer commute even more stressful.

The results of my sensitivity analyses, which excluded single individuals, are presented in Panel B of Table 2.8. I found that although the first-stage F statistics tend to be lower for the married sample, the results are largely consistent with what I found in Panel A. In conclusion, my analysis suggests that while females with children do have a strong preference for a shorter commute, males without children also seem to share this preference, although likely for very different reasons.

Table 2.8: Effects of Commuting on Wages - Parental Status

Panel A: Pooled Sample				
	(1)	(2)	(3)	(4)
Commuting Effect on Wages	0.71*** (0.14)	0.60*** (0.1)	0.56*** (0.09)	0.71*** (0.13)
First-Stage F Statistic	12.94	16.22	16.19	13.31
Panel B: Married Sample				
	(1)	(2)	(3)	(4)
Commuting Effect on Wages	0.78*** (0.17)	0.62*** (0.10)	0.71*** (0.13)	0.76*** (0.14)
First-Stage F Statistic	9.48	16.08	10.33	12.27
Sample	Male, No Children	Male, With Children	Female, No Children	Female, With Children

¹ *p<0.1; **p<0.05; ***p<0.01

² Data Source: ACS 2016.

³ All models include age, age squared, industry, race, education levels, number of children (applicable to samples with children only), whether all children under 14 (applicable to samples with children only), state controls, and the five occupational skill indices.

⁴ All pooled sample analysis includes marital status control.

⁵ The regression is estimated using 2SLS with clustered standard errors regarding working places.

⁶ Full model estimates are available in Appendix J.

Some studies also look at women's commuting dis-utility from an occupation perspective. For instance, Jacob et al. (2019) examines how people's disutility (i.e., dissatisfaction or negative impact) differs with an increase in commuting time, with a particular focus on the effect on women's well-being in areas with thin local labour markets. A thin local labour market refers to an area with limited job opportunities, where it might be chal-

lenging for individuals to find suitable employment options that align with their skills, education, and experience. In such areas, women may face greater difficulties in finding employment opportunities that match their qualifications, preferences, and schedules, making long commutes even more burdensome and stressful. More importantly, it seems that women working full-time and in professional/managerial positions are the ones most affected. To test this theory, I perform similar regressions as in Table 2.4, but on the sub-sample of people working in management occupations only.²³ I display the IV estimate results in Table 2.9. Note that only the normalized cohesion index is used as the instrument. My evidence in models (1) and (2) supports this theory. From the first two columns in Table 2.4, I concluded that male and female workers enjoy similar commuting returns when I look at the pooled sample. However, when estimating the same model with individuals in management positions only, women’s commuting premium increased by 7%, which is almost twice as much as the increase in men’s (4%). This means that female workers working in managerial positions are indeed the ones most affected by commuting and require higher compensations, possibly due to larger reduced well-being. Moreover, models (3) to (6) in Table 2.9 suggest that marital status also plays an important role and should not be ignored when considering the dis-utility theory. In particular, both married male and female managers require higher commuting compensations compared to their pooled counterparts in Table 2.4. Similarly to what I observed in models (1) and (2), married females are compensated 13% more when they work in managerial occupations, much higher than the increase in married males (6%). When I look at single managers, however, the trend is reversed. Compared to the general population, both single male and female managers need less commuting compensation. In fact, both the magnitude and the significance level were reduced for single female managers, contradicting the claim of a decreased utility. Overall, Table 2.9 suggests that for my data, while there exists evidence that female workers working in managerial occupations are impacted the most by commuting times, it is married women who are driving that relationship and dislike commuting the most.

Benefits of Commuting

While commuting is often associated with negative effects such as stress and time constraints, it can also have some benefits. For instance, the literature has suggested that modern workers, especially women, may struggle with overstimulation and a lack of time for personal activities (Schulte, 2019). In this sense, commuting could provide an opportunity for individuals to relax, unwind, and engage in activities that they enjoy, such as reading, listening to music, or simply having some quiet time to themselves. Pindek, Shen, and Andel (2022) hypothesized that people may experience commuting as desired and beneficial “me time”, as the time spent on commuting is less associated with work or home role requirements. More importantly, they documented that individuals with heavier responsibilities in both the work and home domains (for example, busy working parents) tend to have little personal time and thus may value the “commuting me time” more. Similarly,

²³The subsample is constructed using the ACS 2010 Standard Occupational Classification (SOC) system. For reference, please see <https://usa.ipums.org/usa/volii/occtooccsoc18.shtml>.

Table 2.9: Effects of Commuting on Wages - Management Occupation Sub-Sample

<i>Instrumental Variable - Normalized Cohesion Index</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
Commuting Effect on Wages	0.68*** (0.12)	0.71*** (0.11)	0.72*** (0.11)	0.87*** (0.16)	0.47*** (0.11)	0.36** (0.14)
First-Stage F Statistic	18.58	15.74	14.92	11.87	33.56	19.99
Sample	All Male	All Female	Married Male	Married Female	Single Male	Single Female
Marital Status Control	Y	Y	N	N	N	N

¹ *p<0.1; **p<0.05; ***p<0.01

² Data Source: ACS 2016, management occupations only.

³ All models include age, age squared, industry, race, education levels, number of children, whether all children are under 14, state controls, and the five occupational skill indices.

⁴ The regression is estimated using 2SLS with clustered standard errors regarding working places.

⁵ Full model estimates are available in Appendix J.

Jain and Lyons (2008) discussed that time spent on commuting might be the only chance to undertake some personal activities (e.g., listening to the music of one’s personal choice) for some individuals. If this theory fits my data, I should expect to see married individuals, especially females, benefit the most from this positive side of commuting. Hence commuting time should impact their wages less. However, my evidence clearly suggests that married women have the highest commuting returns among all sub-groups, contradicting what the theory predicts. Thus, having “me time” cannot be used to explain my findings.

2.5 Conclusion

This chapter contributes to the literature by incorporating potential instrumental variables to solve the heterogeneity problem associated with commuting times and investigate the causal relationship between commuting times and wages. I use the ACS data from the year 2016 and exploited two potential sources of exogenous variation: city shapes and network connectivity. Although the instruments regarding connectivity turn out to be weak, the normalized cohesion index provides promising results.

Through two-stage least squares (2SLS) estimations with different sub-samples (pooled samples, married individuals, and single ones), I found that the higher commuting effect on wages among women, discovered in my OLS regressions, is not robust. The IV results, which are more reliable than OLS due to addressing potential endogeneity issues, reveal larger estimates, indicating potential bias in OLS regressions. In particular, my OLS analysis indicates that women exhibit higher commuting premium in all sub-samples, whereas the IV estimates show that the commuting premium for the female pooled sample is the same as for men, and that single women actually experience a lower commuting return

compared to single men. My results underscore the importance of gender heterogeneity regarding commuting and highlight potential systematic differences between married and single individuals, emphasizing the superiority of IV over OLS in providing more accurate insights. In Section 2.4.2, I discuss several theories that could potentially explain the different commuting returns regarding gender and marital status I observed in my analysis. Some of these theories are consistent with my data. For example, I find some empirical evidence in my matched couple data suggesting married couples may choose their residential location primarily based on the husband's career opportunities. My evidence also seems to support the assumption that married females have a strong preference for more flexible job arrangements and thus require higher compensation for commuting. Moreover, I find that married women working in management positions seem to be the ones who dislike commuting the most, although men without children also show preferences for shorter commutes. The commuting "me-time" theory turns out to be inconsistent with what I found, and I do not have enough information to verify the assumption about intermediate activities. Overall, married women seem to value time more due to housework and childcare and thus demand higher compensation when they spend time commuting to and from their workplaces. Single women, on the other hand, do not have the same responsibilities as married ones, and that might be one of the main reasons why they have much lower commuting returns.

Chapter 3

Living and Working: Spatial Sorting, Commuting and Wage Inequality

This chapter explores the interplay between job flexibility, residential location sorting, and wage determination. I propose a monocentric model that features a production technology employing both high- and low-skilled workers, a bid-rent approach that determines both the pricing of housing services and the spatial distribution of workers, and a job flexibility parameter that affects commuting costs for high-skilled workers. Since job flexibility influences high-skilled workers' willingness to commute, it ultimately shapes the urban spatial sorting pattern. In settings with low job flexibility, high-skilled workers are inclined to reside near the central business district, earning higher wages that compensate for the opportunity cost of commuting and the high price of real estate at central locations. In contrast, enhanced job flexibility can allow high-skilled workers to relocate to more distant and less expensive areas without facing steep commuting costs, which reduces the equilibrium skill premium.

3.1 Introduction

This study examines the spatial allocation of workers within cities, focusing on the locations of high- and low-skilled workers between urban centers and peripheries and its implications for urban income inequality. Urban settings often highlight disparities in income and wealth, manifesting in a pronounced clustering effect where affluent individuals tend to reside in markedly different locations from less affluent populations. While downtown zones in many cities continue to attract wealthier households (see, for example, Findeisen (2022)), recent observations indicate a suburban migration of this demographic, leading to a “doughnut” effect in real estate wherein suburban markets have outpaced city centre ones (M. J. Delventhal, Kwon, & Parkhomenko, 2021; Ramani & Bloom, 2021).^{1,2} This paper

¹Studies that focus on demographics within metropolitan areas include Buchholz (2022), Couture et al. (2020), Ostermann, Eppelsheimer, Gläser, Haller, and Oertel (2022) and Purtell (2022).

²The “donut effect” is also mentioned in Bond-Smith and McCann (2022) and Gupta, Mittal, Peeters, and Van Nieuwerburgh (2022).

aims to examine the interplay between spatial sorting patterns and urban income inequality, with a particular emphasis on how *job flexibility* influences both factors — a topic less explored in current literature that primarily links inequality to economic agglomeration, city allure for high-skilled workers, and uneven neighbourhood growth.

In my empirical analysis, I leverage data from the 2016 Canadian Census to identify and analyze the spatial sorting patterns of high- and low-skilled workers across cities, employing educational attainment as a metric for skill level. High-skilled individuals are identified as those with at least a bachelor’s degree, whereas low-skilled individuals are the ones without such qualifications. The Canadian Census provides detailed data on commuting distance in kilometres and one-way commuting times in minutes, offering a valuable perspective on spatial sorting patterns and commuting time patterns. Through this lens, cities are categorized into Skill-Central (SC) ones, where high-skilled workers predominantly reside closer to their workplaces compared to low-skilled ones, and Skill-Peripheral (SP) ones, where the opposite trend is present. A critical focus of my analysis is the relationship between spatial sorting patterns and the skill premium across urban environments. I estimate a negative correlation: cities exhibiting an SC pattern, characterized by a lower residence-workplace distance between high- and low-skilled workers, tend to have a higher skill premium.

To elucidate these empirical findings, I propose a theoretical model that outlines the interplay between job flexibility, residential location sorting, and wage determination. The model is based on the monocentric city framework, a classical urban economics structure featuring a single central business district (CBD) where employment opportunities are concentrated. Within this structure, housing prices and worker distribution are determined by the bid-rent approach, where housing services are supplied to those with the highest willingness to pay. The model also incorporates a production technology employing both high- and low-skilled workers. Consequently, the equilibrium wages must entice a workforce possessing the appropriate skill composition to reside within the city and bear the associated commuting costs.

A critical component of my model is the *job flexibility* parameter, which influences the commuting costs and the residential location choices for high-skilled workers. This flexibility can manifest in various forms, such as remote work, flexible hours, or the ability to choose work locations. Remote working has attracted much attention since the pandemic, with a general consensus that workers tend to relocate to rural areas due to the ability to work from home (J. Brueckner, Kahn, & Lin, 2021; M. Delventhal & Parkhomenko, 2020; M. J. Delventhal et al., 2021). However, the nuances between different skill levels regarding job flexibility remain underexplored.³ I argue that while high-skilled workers might have job roles conducive to additional flexibility, low-skilled workers often lack the luxury of remote work due to the manual or consumer-facing nature of their jobs and less access to the digital tools and technology infrastructure needed for remote work.

³Studies like Lewandowski, Lipowska, and Smoter (2022) demonstrated workers’ willingness to forego wages in exchange for flexibility and the employer’s incentive to reduce the salaries for remote workers. However, they do not consider distinctions between high- and low-skilled jobs or explore the correlation between education/skill levels and remote working capabilities.

In this refined framework, limited job flexibility motivates high-skilled workers to reside near the central business district (CBD) to avoid the high opportunity costs associated with commuting, resulting in a skill-central (SC) spatial pattern. Conversely, enhanced job flexibility reduces commuting burdens for high-skilled workers, making suburban areas more appealing and fostering a skill-peripheral (SP) distribution, where high-skilled workers opt to reside at greater distances from CBD. The model further posits that wage structures are endogenous and are influenced by the firm’s strategic decisions to optimize workforce composition for profit maximization. This implies that the equilibrium skill premium is contingent on various factors, including commuting costs and job flexibility, thus influencing workers’ location choices and, ultimately, the urban spatial sorting. Consequently, cities characterized by an SP pattern tend to have a lower equilibrium skill premium compared to cities with an SC pattern, as the flexibility of high-skilled jobs makes it relatively cheaper for firms to attract high-skilled workers. Through numerical solutions, I illustrate the negative relationship between the flexibility of high-skilled jobs and the skill premium, which is consistent with the empirical evidence.

Through a synthesis of empirical and theoretical approaches, this chapter not only contributes to the understanding of urban spatial sorting and income inequality but also provides practical insights for urban planners and policymakers. It emphasizes the importance of job flexibility in shaping urban landscapes. Following this introduction, the chapter proceeds as follows: Section 3.2 reviews relevant literature, Section 3.3 presents empirical evidence from the 2016 Canadian Census, Section 3.4 outlines the theoretical model and its solutions, Section 3.5 discusses the numerical results, and Section 3.6 concludes the chapter.

3.2 Related Literature

Existing literature on urban income inequality primarily attributes this phenomenon to factors like economic agglomeration, which disproportionately enhances the productivity of high-skilled workers (Eliasson & Westerlund, 2022), the gravitational pull of large cities on high-skilled individuals (Lüttge, 2022), and disparities in neighbourhood development (Lynge et al., 2022). These perspectives are supported by findings such as those from Donegan and Lowe (2008), who report a positive correlation between income inequality and the extent of a city’s creative talent pool, and Baum-Snow and Pavan (2013), who observe a strong relationship between wage disparities and city population size.⁴ This paper goes beyond these established narratives by investigating the interplay between the dynamic demographic allocation within metropolitan areas and income inequality, positing job flexibility as a pivotal mechanism connecting these elements.

To the best of my knowledge, few studies have specifically addressed the relevance of workplace flexibility for inequality and spatial sorting. Much of the existing literature focuses on multiple cities. For instance, Diamond and Gaubert (2022) explores the

⁴See also Ahlfeldt, Redding, Sturm, and Wolf (2015), Almeida, Araújo, and Gonçalves (2022), D. Autor (2019) and Behrens, Duranton, and Robert-Nicoud (2014).

relationship between inequality and spatial sorting patterns by employing a model that accounts for differences among workers' skill levels. However, their research primarily examines workers' spatial sorting of workers by skill level across multiple cities in the United States, while my study zeroes in on a single-city scenario with a particular interest in workplace flexibility. Furthermore, unlike the broader, multi-city focus in Diamond and Gaubert (2022), which centers on the distribution of economic activities, my approach uses a monocentric city model, examining the centralization of economic activity within one urban area. Additionally, their emphasis on productivity and amenities diverges from my focus on workplace flexibility. A study closely related to ours is Davis, Ghent, and Gregory (2021), in which the authors focus on working-from-home technology and the productivity elasticity between remote and on-site working. While the amount of remote working is endogenously determined in Davis et al. (2021), I use exogenous flexibility to infer spatial sorting patterns. Tabuchi (2022) also propose a structural monocentric city model featuring different income groups, the housing market, and commuting time. However, their paper considers income as exogenous, while I incorporate an endogenous labour market to demonstrate how employment and wages respond to workplace flexibility.

Perhaps the paper most closely related to ours is Gokan, Kichko, Matheson, and Thisse (2022), which also utilizes a monocentric city model and considers an endogenous labour market. However, there are important differences between my study and theirs. Firstly, the two papers examine different mechanisms for wage adjustments. Gokan et al. (2022) channel the production market within the city and consumption as the primary drivers of income inequality. Specifically, they argue that the proportion of workers working from home (WFH) directly impacts the demand for local consumption services (LCS) from high-skilled workers, pushing low-skilled workers from LCS towards the end product production and lowering their wages. In other words, the skill premium increases stem from the disadvantages low-skilled labour has to bear from a lack of demand from high-skilled labour. The wage premium equation is thus directly impacted by the WFH indicator. In contrast, my research emphasizes how high-skilled workers use their job flexibility to relocate to suburban areas with lower living costs. This relocation allows them to accept lower wages since they save on commuting costs. In my model, changes in wage premiums arise from these broader labour market adjustments rather than direct changes in the wage structure due to WFH practices. The flexibility parameter in my model influences where high-skilled workers choose to live and work, but it does not directly determine the changes in their wages. Instead, it affects the overall labour market, which in turn influences wage structures.

My model predicts the opposite relationship between wage premiums and remote working allocations among high-skilled workers compared to Gokan et al. (2022). Their model predicts that wage premiums will increase with more remote working for high-skilled workers, while mine predicts a decrease. I view Gokan et al. (2022) as a valuable complement to my paper, as the two papers examine a similar issue but with different focuses and perspectives. Reality likely combines elements of both models: on the one hand, the shift towards remote work can reduce demand for LCS, potentially pushing low-skilled labour toward other sectors that may not offer the same wage levels or job stability. On the other hand, broader labour market adjustments, such as changes in wage structures to account

for decreased commuting costs and altered living expenses, will likely materialize simultaneously. These adjustments and changes reflect the economic theories that suggest labour markets evolve in response to shifts in worker behaviour and economic conditions (Moretti, 2012).

Empirical evidence indicating that WFH during the COVID-19 pandemic has exacerbated income inequality supports the need to consider these long-term adjustments (see, for example, Palomino, Rodríguez, and Sebastian (2020), Bonacini, Gallo, and Scicchitano (2021) and Kosteas, Renna, and Scicchitano (2022)). Moreover, real-world corporate practices provide further insight into these trends. For instance, major technology firms like Facebook have begun considering adjustments to employee compensation based on residential locations, reflecting a recognition of the changes in living costs (M. Murphy, 2020). This evolution in compensation strategies underscores the relevance of my model.

3.3 Motivating Evidence

3.3.1 Two Types of Cities

The majority of the literature discussing spatial sorting tends to focus on the evolution of one city over time. For example, Couture and Handbury (2019) document the increasing proportion of college-educated people near city centres, while Couture et al. (2020) estimate a rising propensity to live downtown between the years 1970 and 2014. I, instead, focus on cross-city data from the same year and emphasize the co-existence of cities with different spatial allocations.

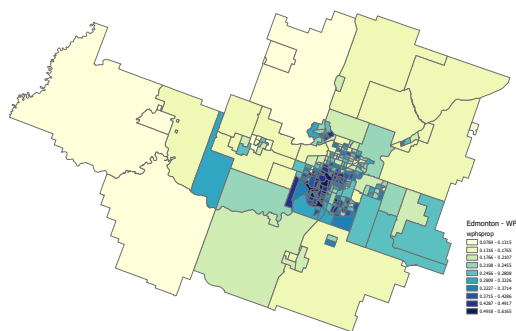
My data come from the long-form Canadian Census of Population 2016.⁵ The Census Program, managed by Statistics Canada, is conducted every five years and provides valuable statistical portraits of Canada (Statistics Canada, 2021). The long-form Census data have detailed demographic and geographic information, which allows me to visualize the spatial allocation patterns by city.⁶

Using this data, I look at the spatial sorting patterns for people who live and work in the same city. Figure 3.1 shows the proportion of the high-skilled⁷ population by census tract for Edmonton and Oshawa, respectively. Panels (a) and (c) display the proportions based on individuals' working locations, while panels (b) and (d) show the same proportions by people's residential places. The darker colours on the map indicate higher proportions of high-skilled individuals. The two cities reveal very different spatial sorting patterns. In Edmonton, high-skilled people tend to locate close to where they work, and panels (a) and (b) look very similar. However, for Oshawa, it is evident that high-skilled people tend to live in different places from where they work. In particular, it appears that, despite working in the centre, many high-skilled individuals live closer to the periphery of the city.

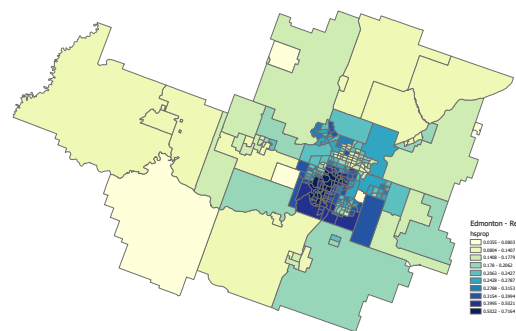
⁵<https://www12.statcan.gc.ca/census-recensement/index-eng.cfm>

⁶Unfortunately, ACS does not contain information on residence-workplace distance information, which is one of the key element utilized to motivate my model.

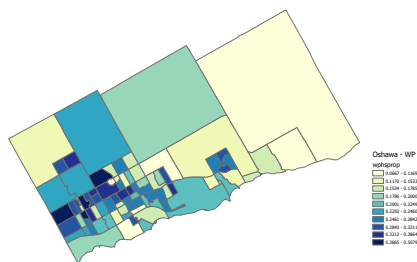
⁷High-skilled individuals are identified as people with at least Bachelor's degrees.



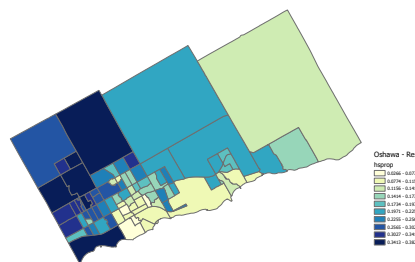
(a) Edmonton - Workplace



(b) Edmonton - Residential



(c) Oshawa - Workplace



(d) Oshawa - Residential

Figure 3.1: Spatial Sorting Patterns - Canada

The patterns revealed by the Canadian Census can also be detected using U.S. data. Figure 3.2 illustrates the density of highly-educated adults⁸ by zip code in two U.S. cities: Houston and New York.⁹ Darker coloured blocks represent the ones with higher high-skilled percentages by residence. The graphs are generated using data from the 2012-16 American Community Survey, which is one of the most extensive ongoing household surveys conducted by the U.S. Census Bureau (U.S. Census Bureau, 2018b).¹⁰ Houston clearly reveals a different spatial sorting pattern than New York. In particular, while highly educated people appear to be concentrated near the centre of Houston, New York shows a somewhat contradictory pattern, where many high-skilled people live further away from downtown.

Drawing on the findings from the Canadian data, I identify two distinct spatial sorting patterns exemplified by Edmonton and Oshawa within the 35 Canadian Central Metropolitan Areas (CMAs). According to Statistics Canada (2018a), a CMA must have a total population of at least 100,000, of which 50,000 or more must live in the central population centre.¹¹ Past literature tends to differentiate cities either by their population (Eeckhout, Pinheiro, & Schmidheiny, 2014), or industrial distribution (Donegan & Lowe, 2008). I, on the other hand, separate cities by the mean residence-workplace distance ratio between high-skilled and low-skilled workers.¹² I hereafter refer to this ratio as the Residence-Workplace (RW) ratio:

$$RWratio_c = \frac{\overline{RW}_{c,h}}{\overline{RW}_{c,l}},$$

where $\overline{RW}_{c,h}$ represents the average residence-to-workplace distance for high-skilled workers, and $\overline{RW}_{c,l}$ denotes the analogous distance for their low-skilled counterparts. I view the RW ratio as a proxy for the city's spatial sorting pattern. Referring back to Figure 3.1, in cities resembling Edmonton, I can observe that a higher proportion of high-skilled workers live and work within the central areas. In such cities, high-skilled workers likely reside closer to their workplaces compared to their low-skilled counterparts. On the contrary, for places like Oshawa, highly educated people are likely to live relatively further away, resulting in a higher RW ratio.

3.3.2 The Difference between the Two Types

City Structure and Inequality

To delve deeper into the relationship between city structure and inequality, I examine the connection between the RW ratio and skill premium. In order to better isolate the most

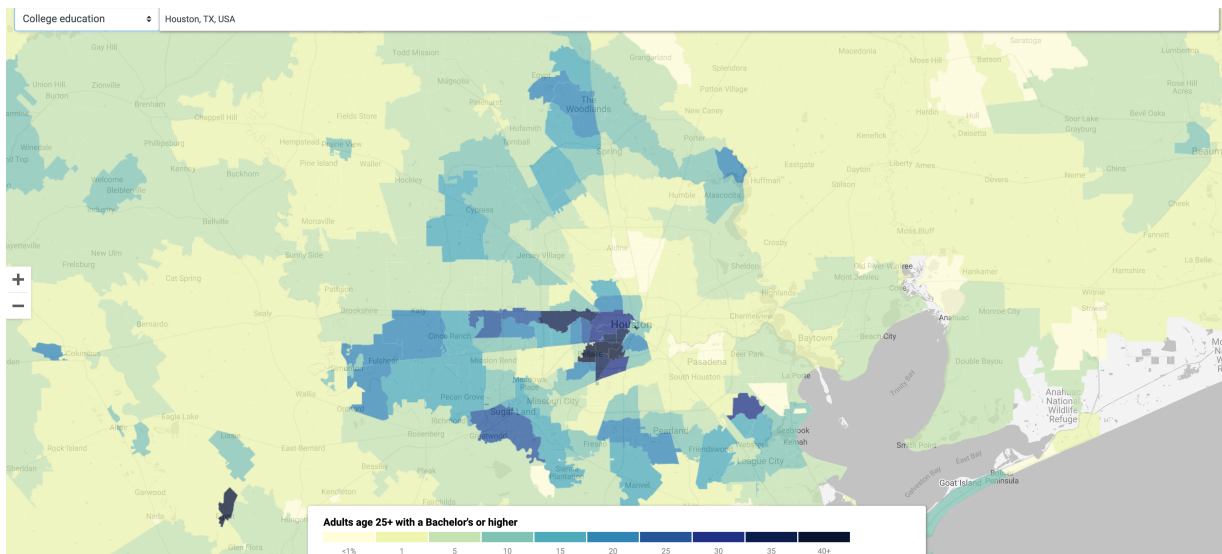
⁸Age 25 and above with bachelor's or higher degrees.

⁹Retrieved from <https://richblockspoorblocks.com/>

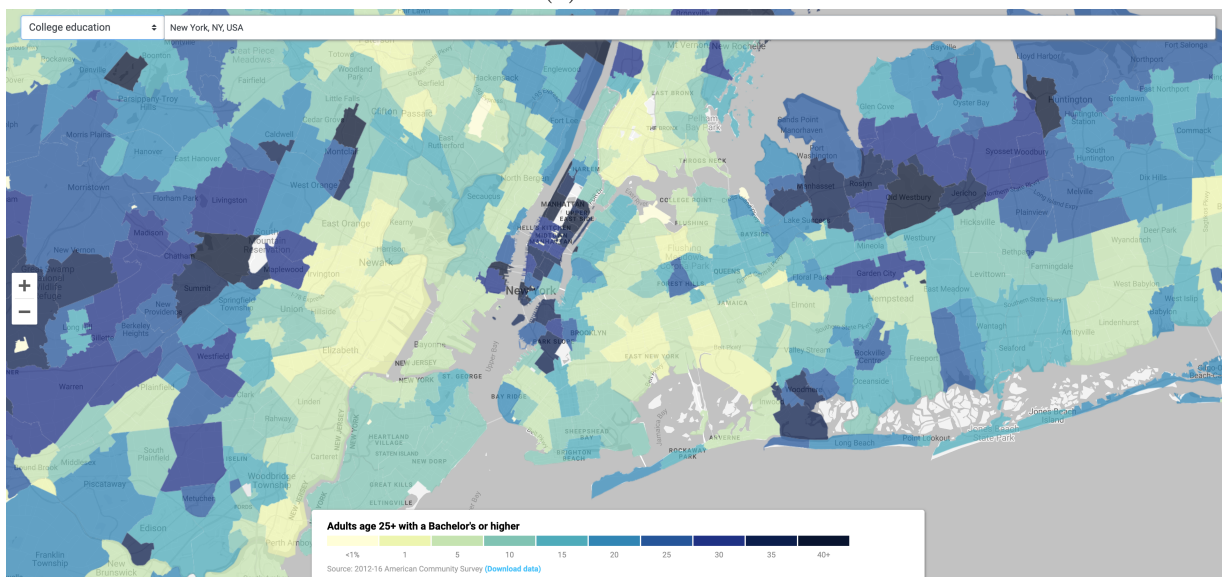
¹⁰According to U.S. Census Bureau, over 3.5 million households across the country are contacted every year to participate in the ACS (U.S. Census Bureau, 2019b).

¹¹A population centre is defined to be an area with a population of at least 1,000 persons per square kilometre (Statistics Canada, 2018b).

¹²The sample used is observations who work in the targeted CMA. High-skilled workers are defined as people with Bachelor's degrees or higher.



(a) Houston



(b) New York

Figure 3.2: Spatial Sorting Patterns - U.S.

salient aspects of this relationship, I focus on specific industries that are more likely to be located downtown. My analysis concentrates on individuals with at least a bachelor's degree working in the finance industry and those with less than a bachelor's degree employed in retail. Furthermore, I restrict my sample to individuals between 30 and 40 years old and working in the top 10 Canadian cities ranked by their working population. To assess the skill premium across different cities, I divide the average wages for high-skilled workers by that of the low-skilled workers within each city's sub-sample.

Figure 3.3 presents the scatter plot illustrating the relationship between the RW ratio of each city and their skill premium. The plot reveals a distinct negative correlation, indicating that as the RW ratio increases, the skill premium decreases. This observation implies that, compared to high-skilled workers in cities where they live farther from the centre, high-skilled individuals in cities with central skilled-worker concentration tend to enjoy higher wage premiums.

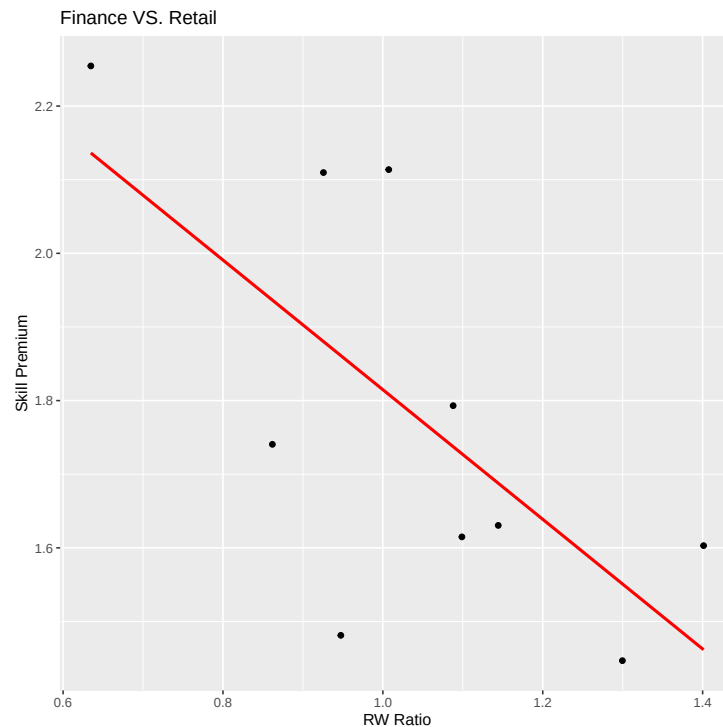


Figure 3.3: Residential-Workplace Ratio and Skill Premium by City

City Structure and Flexibility

I classify Canadian cities based on their RW ratios in relation to unity. Specifically, CMAs with RW ratios less than 1 are defined as the Skill-Central (SC) cities, while the rest are categorized as the Skill-Peripheral (SP) cities. In SC cities, high-skilled workers typically reside closer to their workplaces than low-skilled workers. Conversely, SP cities display the opposite trend. To the best of my knowledge, this is the first paper that categorizes cities

this way.¹³

Among the 35 Canadian CMAs, 13 of them are SC cities, and 22 are SP cities (refer to Appendix K for the complete list of CMAs and their city classification). Table 3.1 documents the summary statistics for the two groups, estimated by the weighted average.¹⁴ Table 3.1 illustrates that SC cities typically have larger populations and higher proportions of high-skilled workers, while SP cities are generally smaller with a greater presence of low-skilled workers. Note that CT stands for commuting time, and the CT ratio in the last row is calculated by taking the ratio between the average commuting time of high-skilled and low-skilled workers. Intriguingly, the average RW ratio and CT ratio suggest that high-skilled individuals, despite residing notably closer to their workplaces in SC cities, have commute durations comparable to their low-skilled counterparts. I interpret this as evidence of workplace flexibility. It is plausible that high-skilled workers residing in SP cities possess greater autonomy and flexibility in determining when or if they need to commute to work. As a result, they can avoid high-peak hours, effectively reducing their commuting time.¹⁵

Table 3.1: Summary Statistics for SC and SP Cities

	SC	SP	Significant ² ?
N	13	22	N/A
Population	465,945	68,774	Yes
High-Skilled ³ Prop	40.08%	29.26%	Yes
RW Ratio	0.91	1.16	Yes
CT ⁴ Ratio	1.02	0.98	No

¹ Source: Canadian Census 2016;

² The significance levels are tested using two-sample t tests;

³ High-skilled: higher than or equal to bachelor's degrees;

⁴ Commuting time is measured one way in minutes.

The above empirical evidence motivates me to seek a framework that incorporates wage inequality and spatial sorting simultaneously. I therefore propose a model based on the monocentric city structure. Literature on within-city spatial sorting typically features exogenous wage distribution and homogeneous labour (Allen, Arkolakis, & Li, 2015; Couture et al., 2020; Li, 2021). I, on the other hand, introduce an endogenous labour market, which allows me to examine city structure, inequality and job flexibility in an urban setting.

¹³Edmonton has a RW ratio of 0.81, and the RW ratio for Oshawa is 1.14, as predicted in Section 3.3.1.

¹⁴The applied weights are the cities' populations.

¹⁵Although the concept of flexibility is inherently complex, making it challenging to obtain direct evidence of its relationship with the RW ratio for high-skilled workers, I believe that comparing commuting time and commuting distance offers valuable indirect evidence.

3.4 Model

I consider a city represented by a line segment, the length of which, X , is endogenously determined.¹⁶ The Central Business District (CBD), where all jobs are located, is at the origin (point zero). Both high-skilled and low-skilled labour can choose to locate in the city.

3.4.1 Consumer's Problem

When choosing to locate and work in the city, workers travel a distance x from their residential locations to the CBD, and their commuting cost function is defined to be

$$T_i(x) = tx + \rho_i w_i x, \quad i \in \{l, h\}.$$

In the above equation, t stands for the linear commuting cost workers have to bear for every unit of distance; ρ_i is the flexibility parameter that specifies the opportunity cost for spending time on the road,¹⁷ and w_i is the wage rate received by the worker who belongs to the skill-level group i (l stands for low-skilled, and h stands for high-skilled). Past literature has found that high-skilled workers are more likely to benefit from flexible schedules and increased job autonomy. In contrast, individuals with lower incomes and education levels typically cannot work from home and often lack flexible working hours (Bick et al., 2020; Stantcheva, 2021; Ecke et al., 2022). As such, I set ρ_h to be less than ρ_l . In other words, high-skilled workers are better able to reduce their commuting costs, presumably by travelling at off-peak times or working from home.

Consumers allocate their disposable income (wage minus commuting cost) between consumption c and housing service s . The price of housing services, which depends on x , is denoted by $p(x)$, and the price of non-housing consumption is normalized to 1. The consumer's utility function is given by:

$$U_i(x) = 1 + c_i(x) + \log(s_i)$$

$i \in \{l, h\}$. Note that the constant 1 in the utility function serves to simplify the analysis. By doing so, it avoids the need to include a “ -1 ” in all subsequent expressions for the indirect utility function $V(x)$. This normalization does not affect the optimization problem, as it shifts the utility function upward uniformly without altering the marginal utilities or optimal choices.

The consumer's problem at different locations x can be described as follows:

$$\begin{aligned} V_i(x) \equiv \max_{c_i \geq 0, s_i \geq 0} \quad & 1 + c_i + \log(s_i) \\ \text{s.t.} \quad & c_i + p(x)s_i \leq w_i - (tx + \rho_i w_i x) \end{aligned}$$

¹⁶The monocentric city model initially considers the city to be a circle. In my model, a circle and a line are functionally equivalent because my primary focus is on the distance to the CBD.

¹⁷Note that I have normalized the speed to be 1.

$i \in \{l, h\}$. The first-order conditions are

$$\begin{aligned} s_i^*(x) &= \frac{1}{p(x)} \\ c_i^*(x) &= w_i - (tx + \rho_i w_i x) - 1 \end{aligned} \tag{3.4.1.1}$$

Therefore, the indirect utility function becomes:

$$V_i(x) = w_i - (tx + \rho_i w_i x) - \log(p(x)), \quad i \in \{l, h\}. \tag{3.4.1.2}$$

The Bid Function Approach

Building upon the work of Rosen (1974) and Ellickson (1981), I define the bid function $P_i : [0, X] \rightarrow \mathbb{R}^+$ as the price of housing services that yields a utility level $\bar{V}_i$ for a consumer of type i . The bid function approach is rooted in hedonic pricing theory, which posits that the price of a good, such as housing, is determined by the value of its characteristics or attributes. In the context of urban housing markets, the bid function captures the maximum amount a consumer is willing to pay for one unit of housing, considering its location and the consumer's preferences and income.

In my model, I compare the bid functions for high-skilled and low-skilled workers to determine which type will reside at a given distance $x \in [0, X]$. For example, if $P_h(x) > P_l(x)$, then high-skilled workers will be willing to pay more. As a result, they will end up living at distance x . This approach allows me to investigate how distance to the Central Business District (CBD) affects the market price of housing and predict changes in skill distribution and urban spatial patterns. By defining the bid function in this manner and incorporating the comparison between high-skilled and low-skilled workers' bid functions, I can analyze the housing market while accounting for consumer heterogeneity.

By equation (3.4.1.2),

$$w_i - (tx + \rho_i w_i x) - \log(P_i(x)) = \bar{V}_i, \quad i \in \{l, h\}.$$

Rearranging the above equation yields

$$P_i(x) = \exp \left\{ w_i - (tx + \rho_i w_i x) - \bar{V}_i \right\}, \quad i \in \{l, h\}. \tag{3.4.1.3}$$

Note that $P_i > 0$, meaning consumers are always willing to pay a positive price for housing services regardless of their type. Also note that

$$\frac{\partial P_i}{\partial x} = \exp \left\{ w_i - (tx + \rho_i w_i x) - \bar{V}_i \right\} \cdot (-(t + \rho_i w_i)) < 0, \quad i \in \{l, h\}. \tag{3.4.1.4}$$

This indicates that for both high-skilled and low-skilled workers, the willingness to pay for housing services goes down as the distance to the CBD increases.

As mentioned before, the bid functions indicate how much a consumer of type i is willing to pay for housing services at a distance x to achieve utility level $\bar{V}_i$. Any price

higher than P_i would yield a strictly lower utility level than $\bar{V}_i$ for consumer type i , keeping everything else constant.

3.4.2 Firm's Problem

I assume perfectly competitive labour markets for high- and low-skilled labour. The representative firm utilizes the Cobb-Douglas production technology and demands low-skilled and high-skilled labour L, H while taking wages, w_l and w_h , as given.

The firm's profit maximization problem can be described as follows:

$$\max_{L, H} AL^\beta H^{1-\beta} - w_l L - w_h H,$$

where $\beta \in (0, 1)$ is the output elasticity for low-skilled labour in production and A is the city-wide productivity; the profit-maximizing firm is incentivized to hire more workers until both the high-skill and low-skill wages equal the marginal productivity of the corresponding worker type. Therefore, the first order conditions give the implicit solution to the labour demands, L^* and H^* :

$$\begin{aligned} w_l &= A\beta \left(\frac{H^*}{L^*} \right)^{1-\beta} \\ w_h &= A(1-\beta) \left(\frac{L^*}{H^*} \right)^\beta \end{aligned} \tag{3.4.2.1}$$

3.4.3 The Builder's Problem and the Supply of Housing Services

Housing services are supplied by a representative builder, taking land units as input. I assume the production of housing service is fixed, and every unit of land is converted into *one* unit of housing service by the builder at no cost. The builder's profit maximization problem can be described as follows:

$$\max_{\gamma(x) \in \{0,1\}} \gamma(x)P_l(x) + (1 - \gamma(x)) P_h(x), \quad \forall x$$

where γ_x indicates the amount of housing services sold to low-skilled workers at location x . Ultimately, the builder decides to whom they will sell the housing services based on the bid-price functions. Consequently, the builder is willing to supply housing services as long as there is demand at a non-negative price. Note that in equilibrium, the total unit of land available is equal to the length of the city, X , which corresponds to the amount of housing services available. Also note that the price of housing services, $p(x)$, is now determined by the consumers' bid functions (equation (3.4.1.3)). Since the developer will always sell the housing service at the highest price possible, we have

$$\gamma(x) = \begin{cases} 1 & \text{if } P_h(x) < P_l(x) \\ 0 & \text{o.w.} \end{cases} \tag{3.4.3.1}$$

and

$$p(x) = \max \{P_h(x), P_l(x)\}, \quad \forall x. \quad (3.4.3.2)$$

3.4.4 Perfect Mobility

In my analysis, I adopt an open-city structure, where both high-skilled and low-skilled individuals can freely enter and locate within the city without restrictions. The wage levels are endogenously determined to ensure both high- and low-skilled workers are willing to live and work in the city. It is important to note that these two types of labour have distinct outside options and are not required to be indifferent across all locations within the city. As mentioned in Section 3.4.3, the builder will invariably choose the type of worker who is willing to pay higher prices for the housing services. Consequently, for each of these two labour types, the price of housing services will either be higher than (when the other type is willing to pay more) or equal to their bid function (when they are the ones paying more).

Given the assumption of free entry into the city, each worker type has an exogenous outside option with values $\bar{V}_h$ and $\bar{V}_l$. In equilibrium, the housing price $p(x)$ must satisfy the condition that no worker type can achieve a higher utility by relocating. Therefore, a price $p(x) < P_i(x)$ (where $P_i(x)$ represents the bid function of worker type i) would result in an influx of workers whose utility would exceed their outside option $\bar{V}_i$, thereby disrupting the optimal allocation between labour types and the corresponding equilibrium. Thus, at any given location x , the utility level each worker type can possibly achieve will either be equal to their outside option $\bar{V}$ or lower. More formally,

$$\begin{aligned} V_i(x) = \bar{V}_i &\Leftrightarrow p(x) = P_i(x), \quad \text{and} \\ V_i(x) < \bar{V}_i &\Leftrightarrow p(x) > P_i(x) \end{aligned} \quad (3.4.4.1)$$

$\forall x \in [0, X]$ and $i \in \{l, h\}$.

3.4.5 Population Density and Market Clearing

The population of low-skilled labour that lives at distance x is determined by the spatial allocation function $\phi(x)$, which represents the proportion of land that is occupied by low-skilled labour at distance x .

The population density function is defined as the number of residents per unit of land at x . Since one unit of housing service is available per unit of land and individuals consume s_i^* units of housing service, the population density at x equals

$$\frac{\phi(x)}{s_l^*(x)} + \frac{1 - \phi(x)}{s_h^*(x)}, \quad \text{for } x \in [0, X]. \quad (3.4.5.1)$$

The products are assumed to be traded in a highly competitive market, allowing for exchanges between regions or cities. Consequently, the goods market does not need to

clear within the city. Furthermore, the housing market trivially clears since the aggregate demand equals the total supply of housing services:

$$\int_0^X \left(\frac{\phi(x)}{s_l^*(x)} s_l^*(x) + \frac{1-\phi(x)}{s_h^*(x)} s_h^*(x) \right) dx = \int_0^X dx = X \quad (3.4.5.2)$$

In the above equation, $\frac{\phi(x)}{s_l^*(x)} s_l^*(x)$ is the product of the number of low-skilled individuals residing at distance x and the per-person demand of housing services. It represents aggregate housing services consumed by the low-skilled population in the city. Similarly, $\frac{1-\phi(x)}{s_h^*(x)} s_h^*(x)$ embodies the equivalent measure for the high-skilled population, reflecting their total demand for housing services. Note that $\phi(x)$ characterizes the spatial allocation within the city.

For the labour market, I have

$$\begin{aligned} L^* &= \int_0^X \frac{\phi(x)}{s_l^*(x)} dx \\ H^* &= \int_0^X \frac{1-\phi(x)}{s_h^*(x)} dx \end{aligned} \quad (3.4.5.3)$$

Each worker supplies their labour endowment (normalized to unity) inelastically. Hence, the labour supply is equivalent to the city population. The prices of labour w_l and w_h , which influence the labour demands, adjust to clear the market for low- and high-skilled labour.

3.4.6 City Size

By equations (3.4.1.1), we observe that $\frac{\partial}{\partial x} c_i^* < 0$. This negative relationship indicates that consumption levels decline as individuals live farther away from the city centre. In simpler terms, people tend to consume less as their distance from the CBD increases. As long as the consumption level $c_i(x)$ is greater than zero, there will be residents at a distance x from the city centre. Therefore, the maximum distance at which worker type i will reside, X_i , is defined by $c_i^*(X_i) = 0$. In other words,

$$X_i = \left\{ \frac{w_i - 1}{t + \rho_i w_i} \right\}, \quad i \in \{h, l\}. \quad (3.4.6.1)$$

Note that $\frac{\partial X_i}{\partial w_i} = \frac{t + \rho_i}{(t + \rho_i w_i)^2} > 0$, which indicates that as the wage rates go up, both types of workers will be willing to live further away. It follows that the city size, X , is defined by

$$X \equiv \max \{X_l, X_h\} = \max_{i \in \{l, h\}} \left\{ \frac{w_i - 1}{t + \rho_i w_i} \right\}. \quad (3.4.6.2)$$

3.4.7 Equilibrium

The equilibrium of my model consists of a set of values $(L^*, H^*, w_l^*, w_h^*, X^*)$ and a set of functions $(c_l^*, s_l^*, c_h^*, s_h^*, P_l^*, P_h^*, p^*, \gamma^*, \phi^*)$ such that:

1. **Optimal Consumption:** consumers demand consumption and housing services optimally according to the first order conditions in (3.4.1.1), $i \in \{l, h\}$;
2. **Firm Profit Maximization:** firms are maximizing their profit with a perfectly competitive market where there are no barriers to entry or exit; w_l^* and w_h^* satisfy equations (3.4.2.1);
3. **Builder Profit Maximization:** the builder supplies housing services optimally and $\gamma^*(x)$ satisfies equation (3.4.3.1) $\forall x \in [0, X^*]$;
4. **Optimal Spatial Allocation:** $\forall x \in [0, X^*]$, when $\phi^*(x) > 0$, $p^*(x) = P_l^*(x)$; and when $\phi^*(x) < 1$, $p^*(x) = P_h^*(x)$; $P_l^*(x)$ and $P_h^*(x)$ satisfy equation (3.4.1.3);
5. **Labour Market Clearing:** L^* and H^* satisfy equations (3.4.5.3);
6. **Housing Market Clearing:** $\gamma^*(x) = \phi^*(x) \forall x \in [0, X^*]$ and X^* satisfies equation (3.4.6.2).

Note that in equilibrium,

$$\phi^*(x) = \begin{cases} 1 & \text{if } P_h(x) < P_l(x) \\ 0 & \text{o.w.} \end{cases} \quad (3.4.7.1)$$

The equilibrium conditions ensure that each agent in the model optimizes her choices based on her preferences. Moreover, the equilibrium prices are such that supply equates to demand in both labour and housing markets.

3.4.8 Model Specifications

It is worth discussing some of the specifications of my model. In particular, the assumption that all jobs are located in the CBD merits attention. Although this simplification does not fully capture the real-world distribution of jobs, it has important implications for understanding the complementary relationship between high-skilled and low-skilled jobs. By focusing on the fact that high-skilled workers need to work downtown, my model emphasizes the necessity of having a market for low-skilled jobs within the same geographical area. Examples of these low-skilled jobs include restaurant workers, building janitors, retail staff, and other service-oriented positions that cater to the needs of high-skilled workers and the businesses they work for (Glaeser, Kolko, & Saiz, 2001).

Secondly, the static nature of my model and the quasi-linear utility function used presents some limitations when it comes to drawing implications for the housing market.

In particular, the model does not account for time-dependent changes such as market conditions, and the utility function may not accurately reflect the complex decision-making processes of consumers. However, my model emphasizes the importance of long-term housing consumption inequality, which is reflected in the different units of housing service acquired by individuals with varying skill levels. For example, in the case of a SP equilibrium, high-skilled individuals are able to increase their consumption of housing service units when they choose to live further away from the CBD. This allows them to gain access to larger, more luxurious housing options as they benefit from the declining housing prices associated with increased distance from the city centre.

Additionally, the monocentric city model I adopt provides a useful framework for understanding the distribution of workers within a single city, but it may not fully capture the complexities of metropolitan areas with multiple job centres or cities that experience substantial urban sprawl (Arribas-Bel & Sanz-Gracia, 2014). Despite these limitations, my model offers valuable insights into the relationships between spatial sorting patterns, skill premiums, and the role of workplace flexibility in influencing these interactions.

Lastly, my model's assumptions regarding workplace flexibility and job autonomy are based on the general trends observed in the labour market. High-skilled workers, such as those in managerial positions or specialized professions, tend to have greater control over their work schedules and the ability to work remotely. However, it is important to recognize that these trends may not be uniform across industries or specific job positions. Further research could explore the effects of variation in workplace flexibility and job autonomy on the spatial sorting patterns and skill premiums observed in different sectors or job types.

3.5 Equilibrium Analysis

Recall that I previously defined two types of spatial sorting patterns: SC and SP. Figure 3.4 provides their illustrations. In equilibrium, one of these two potential patterns will emerge. I now introduce a lemma that characterizes the conditions under which each equilibrium pattern arises, providing a clearer understanding of the factors influencing the spatial sorting outcome. From this point onward, I normalize $\rho_l = 1$.

Lemma 1 *In equilibrium, the spatial sorting pattern is determined by the equilibrium skill premium $\frac{w_h}{w_l}$, and the high-skilled individuals' relative job flexibility ρ_h . If $\frac{w_l}{w_h} < \rho_h$, then the city exhibits the SC pattern, and income decreases with distance from CBD; If $\frac{w_l}{w_h} > \rho_h$, then the city exhibits the SP pattern, and income increases with distance from CBD.*

The lemma states that the equilibrium spatial sorting pattern is determined by the inverse of the equilibrium skill premium, $\frac{w_l}{w_h}$, and the high-skilled individuals' relative job flexibility ρ_h . In essence, the lemma implies that if the high-skilled workers' jobs are flexible enough, then they will choose to reside in the periphery of the city. However, if their jobs are not sufficiently flexible, they will opt to live closer to the city centre. In the next section, I provide the characterization of the equilibrium and the proof of Lemma 1.

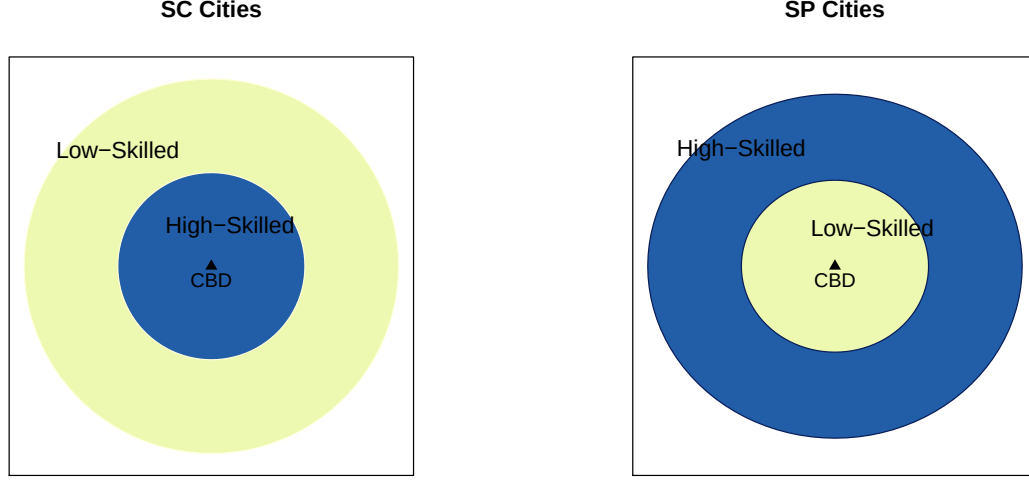


Figure 3.4: Illustration of SC and SP Patterns

3.5.1 Equilibrium Solutions

I begin by demonstrating that the model yields two potential solutions, each corresponding to one type of spatial sorting pattern. However, only one of these solutions will emerge as the equilibrium, depending on the parameter values. I then characterize the systems of equations for each case, highlighting the unique equilibrium corresponding to the prevailing spatial sorting pattern.

Spatial Allocation

Taking w_i and ρ_i as given, I determine the “cut-off” point, x_m , such that $P_l(x_m) = P_h(x_m)$:

$$\begin{aligned}
 P_l(x_m) = P_h(x_m) &\Rightarrow \exp \left\{ w_l - (tx_m + \rho_l w_l x_m) - \bar{V}_l \right\} = \exp \left\{ w_h - (tx_m + \rho_h w_h x) - \bar{V}_h \right\} \\
 &\Rightarrow w_l - (tx_m + \rho_l w_l x_m) - \bar{V}_l = w_h - (tx_m + \rho_h w_h x) - \bar{V}_h \\
 &\Rightarrow x_m = \frac{\Delta w - \Delta \bar{V}}{\Delta \rho w}
 \end{aligned} \tag{3.5.1.1}$$

where $\Delta w \equiv w_h - w_l$, $\Delta \bar{V} \equiv \bar{V}_h - \bar{V}_l$ and $\Delta \rho w \equiv \rho_h w_h - \rho_l w_l$.

To determine the spatial allocation, I take the derivative of the bid-price functions with respect to x and evaluate the derivatives at x_m . As illustrated in Figure 3.5, panel (a), if

$$\left. \frac{\partial P_h}{\partial x} \right|_{x=x_m} = -P_h(x_m)(t + \rho_h w_h) < -P_l(x_m)(t + \rho_l w_l) = \left. \frac{\partial P_l}{\partial x} \right|_{x=x_m},$$

then low-skilled labour’s willingness to pay for housing services is higher than the high-skilled ones for all distances $x > x_m$. Therefore, low-skilled workers will live further away

from the city centre. Otherwise, high-skilled labour lives in suburban areas, as illustrated in Figure 3.5, panel (b).

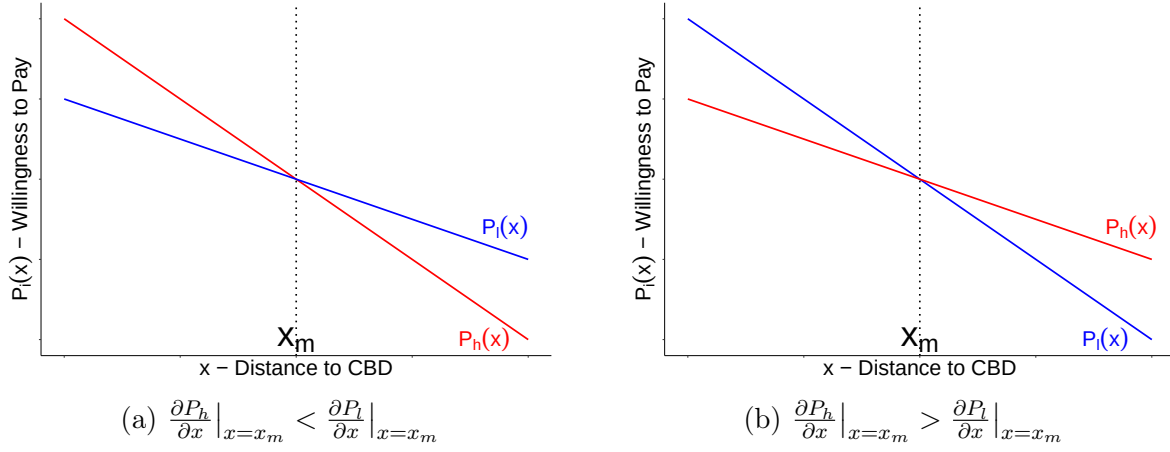


Figure 3.5: Spatial Allocation Patterns

It follows that, by taking the formula for x_m derived in equation (3.5.1.1) and substituting it into inequalities (3.4.1.4),

$$\frac{\partial P_h}{\partial x} \Big|_{x=x_m} \leq \frac{\partial P_l}{\partial x} \Big|_{x=x_m} \Leftrightarrow 0 \leq \Delta \rho w. \quad (3.5.1.2)$$

Since the above condition holds for any x_m satisfying $P_l(x_m) = P_h(x_m)$, and P_l and P_h are monotonic, P_l and P_h can cross at most once when inequality (3.5.1.2) is strict. Note that (3.5.1.2) provides the determining condition for the specific equilibrium that emerges from my model. Although one might consider the niche case where only one type of labour resides in the city, resulting in zero output and wages, this scenario is not possible in equilibrium. The endogenous wage adjustments ensure that both high- and low-skilled workers reside in the city, maintaining a workforce composition that supports profit-maximizing production. In the subsequent sections, I will examine each case and establish the requisite conditions to ensure the presence of both types of workers within the city to achieve equilibrium.

Case 1: $\Delta \rho w > 0$

$$\phi(x) = \begin{cases} 0 & \text{if } x \in \left[0, \frac{\Delta w - \Delta \bar{V}}{\Delta \rho w}\right] \\ 1 & \text{o.w.} \end{cases} \quad (3.5.1.3)$$

For both types of labour to locate in the city, I need $x_m \in (0, X_l]$, which implies¹⁸

$$0 < \frac{\Delta w - \Delta \bar{V}}{\Delta \rho w} < \frac{w_l - 1}{t + \rho_l w_l} \quad (3.5.1.4)$$

¹⁸ X_l and X_h are defined in equation (3.4.6.1).

Case 2: $\Delta\rho w < 0$

$$\phi(x) = \begin{cases} 1 & \text{if } x \in \left[0, \frac{\Delta w - \Delta \bar{V}}{\Delta \rho w}\right) \\ 0 & \text{o.w.} \end{cases} \quad (3.5.1.5)$$

For both types of labour to locate in the city, I need $x_m \in (0, X_h]$, which implies

$$0 < \frac{\Delta w - \Delta \bar{V}}{\Delta \rho w} < \frac{w_h - 1}{t + \rho_h w_h} \quad (3.5.1.6)$$

With ρ_l normalized to unity, the sign of $\rho_h w_h - \rho_l w_l$ ultimately boils down to the difference between the relative flexibility of high-skill jobs, ρ_h , and the inverse of the skill premium, $\frac{w_l}{w_h}$. In equilibrium, this difference determines the spatial sorting pattern. If the high-skill jobs are sufficiently flexible that ρ_h is smaller than the inverse of skill premium, then $\Delta\rho w < 0$ (case 2) and high-skilled individuals will live in the suburban areas. However, if $\rho_h > \frac{w_l}{w_h}$ (case 1), then it is the low-skilled workers who live near the peripheral.

For the knife-edge scenario where $\Delta\rho w = 0$, the function $\phi(x)$ can take on any value in the interval $[0, 1]$ for all $x \in [0, X]$. There will be no identifiable spatial sorting pattern within the city, as every location can potentially host both types of labour. It is worth noting that this case is less intriguing from an analytical standpoint and is referenced here only for the sake of completeness.

Equilibrium Solutions Given Maximum Radius

By equations (3.4.1.1), (3.4.1.3) and (3.4.3.2), the population density function (equation (3.4.5.1)) can be expressed as

$$\phi(x) \exp \left\{ w_l - (tx + \rho_l w_l x) - \bar{V}_l \right\} + (1 - \phi(x)) \exp \left\{ w_h - (tx + \rho_h w_h x) - \bar{V}_h \right\}.$$

Recall that $\phi(x)$ is defined in equations (3.5.1.3) and (3.5.1.5) and determines the spatial pattern within the city. This function thus captures how the high-skilled and low-skilled workers are spatially distributed across the city. This distribution, in turn, influences the equilibrium analysis, as established in the following sections.

Equilibrium 1: when $\frac{w_l}{w_h} < \rho_h$, the model yields the SC pattern equilibrium.

Based on the labour market clearing condition (3.4.5.3), the endogenous city size (equation (3.4.6.2)) and the spatial allocation condition (3.5.1.3), it follows that

$$\begin{aligned}
L^* &= \int_0^X \frac{\phi(x)}{s_l^*(x)} dx = \int_{x_m}^{X_l} \phi(x) P_l(x) dx \\
&= \frac{1}{t + \rho_l w_l} \cdot \left(\exp \left\{ w_l - \bar{V}_l - \frac{(\Delta w - \Delta \bar{V})(t + \rho_l w_l)}{\Delta \rho w} \right\} - \exp \left\{ 1 - \bar{V}_l \right\} \right) \\
H^* &= \int_0^X \frac{1 - \phi(x)}{s_h^*(x)} dx = \int_0^{x_m} (1 - \phi(x)) P_h(x) dx \\
&= \frac{1}{t + \rho_h w_h} \cdot \left(\exp \left\{ w_h - \bar{V}_h \right\} - \exp \left\{ w_h - \bar{V}_h - \frac{(\Delta w - \Delta \bar{V})(t + \rho_h w_h)}{\Delta \rho w} \right\} \right)
\end{aligned} \tag{3.5.1.7}$$

Note that $L^* > 0$ is guaranteed by condition (3.5.1.4). Equations (3.5.1.7) and (3.4.2.1) jointly determine w_l^* , w_h^* , L^* and H^* as functions of A, β, t, ρ_i and $\bar{V}_i$.

Equilibrium 2: when $\frac{w_l}{w_h} > \rho_h$, the model yields the SP pattern equilibrium.

Based on the labour market clearing condition (3.4.5.3), the endogenous city size (equation (3.4.6.2)) and the spatial allocation condition 3.5.1.5, it follows that

$$\begin{aligned}
L^* &= \int_0^X \frac{\phi(x)}{s_l^*(x)} dx = \int_0^{x_m} \phi(x) P_l(x) dx \\
&= \frac{1}{t + \rho_l w_l} \cdot \left(\exp \left\{ w_l - \bar{V}_l \right\} - \exp \left\{ w_l - \bar{V}_l - \frac{(\Delta w - \Delta \bar{V})(t + \rho_l w_l)}{\Delta \rho w} \right\} \right) \\
H^* &= \int_0^X \frac{1 - \phi(x)}{s_h^*(x)} dx = \int_{x_m}^{X_h} (1 - \phi(x)) P_h(x) dx \\
&= \frac{1}{t + \rho_h w_h} \cdot \left(\exp \left\{ w_h - \bar{V}_h - \frac{(\Delta w - \Delta \bar{V})(t + \rho_h w_h)}{\Delta \rho w} \right\} - \exp \left\{ 1 - \bar{V}_h \right\} \right)
\end{aligned} \tag{3.5.1.8}$$

Note that $H^* > 0$ is guaranteed by condition (3.5.1.6). Equations (3.5.1.8) and (3.4.2.1) jointly determine w_l^* and w_h^* , L^* and H^* as functions of A, β, t, ρ_i and $\bar{V}_i$ ¹⁹.

¹⁹For a comprehensive explanation of the calculation process, please refer to the Appendix L.

In this section, I have derived the equilibrium solutions based on the market-clearing conditions and spatial allocation determinants. Specifically, I have shown that the spatial distribution of high- and low-skilled workers within the city hinges on the slope of their bid price functions at the “cut-off” point, x_m , where the two bid price functions are equal. This further implies that the determinant of the sorting pattern is the relative magnitude of the difference in flexibility of high-skilled jobs, ρ_h , and the inverse of the skill premium, $\frac{w_l}{w_h}$. Specifically, when $\rho_h > \frac{w_l}{w_h}$, limited job flexibility motivates high-skilled workers to reside near the CBD to avoid high commuting costs, resulting in low-skilled workers settling further from the city center and a skill-central (SC) pattern. In the opposite scenario, enhanced job flexibility reduces commuting burdens, making suburban living more attractive to high-skilled individuals. As a result, high-skilled workers gravitate towards suburban locales, leading to a skill-peripheral (SP) spatial pattern. In each type of equilibrium, the wage structures are endogenously determined to ensure the optimal composition of the workforce, with the equilibrium skill premium reflecting commuting costs and job flexibility. In summary, the model mechanisms highlight how the equilibrium skill premium must entice high- and low-skilled workers to live, work, and commute in the city, which is how job flexibility interacts with urban inequality and spatial sorting.

3.5.2 Model Simulation Results

This section documents the numerical solution of my model. In particular, I focus on the outcomes resulting from varying the flexibility parameter, ρ_h . Table 3.2 describes the parameters used when performing the computation. Note that these variables, apart from ρ_h , are all kept constant. $\bar{V}_l$ is normalized to zero, and $\bar{V}_h$ is set such that the skill composition in equilibrium reflects the aggression of workers with a university degree.

Table 3.2: Simulation Parameter Setup

parameter	definition	value
A	city-wide production technology	20
t	linear commuting cost	0.1
ρ_l	low skilled job flexibility	1
ρ_h	high skilled job flexibility	(0,1)
β	output elasticity for low-skilled labour	0.4
$\bar{V}_l$	low skilled outside option	0
$\bar{V}_h$	high skilled outside option	5

3.5.3 Two Types of Equilibrium

I solve the model by equating demands in equations (3.4.2.1) with labour supply in equations (3.5.1.7) and (3.5.1.8), using the parameter values reported in Table 3.2. I vary ρ_h while keeping all other parameters constant and then determine the unique equilibrium for

each respective case. I found that the system of equations produces the SC city scenario when $\rho_h > 0.6$ and switches to the SP city equilibrium when $\rho_h < 0.6$ under the current setting. In other words, a large value of ρ_h leads to the clustering of high-skilled people in the city centre, while a small ρ_h results in a SP city, where high-skilled labour locates further away from the CBD.

3.5.4 Comparative Statics

Figure 3.6 and 3.7 illustrates the changes in w_h and w_l as ρ_h decreases. The dotted blue line indicates the cut-off point where the type of equilibrium changes, with SC patterns on the left of the blue line and SP ones on the right. As high-skill jobs become more flexible, the wages for high-skilled workers decrease, whereas low-skilled workers are paid more. As a result, the skill premium, $\frac{w_h}{w_l}$, increases with ρ_h as demonstrated in Figure 3.8. This finding aligns with the empirical evidence presented in Section 3.3.2, where I demonstrated the negative relationship between the city-wise RW ratio and skill premium.

In that section, cities with RW ratios greater than 1 are inferred to exhibit a spatial sorting pattern consistent with the SP equilibrium, where high-skilled workers reside at the city's periphery, and low-skilled workers inhabit the city centre. Conversely, those with RW ratios less than 1 are inclined towards the SC pattern, with the spatial patterns reversed. It is worth noting that while we do not have direct evidence that cities with RW ratios greater than 1 definitively exhibit the SP equilibrium or that those with RW ratios less than 1 follow the SC pattern, the RW ratio serves as a robust proxy supporting the theoretical predictions of my model.

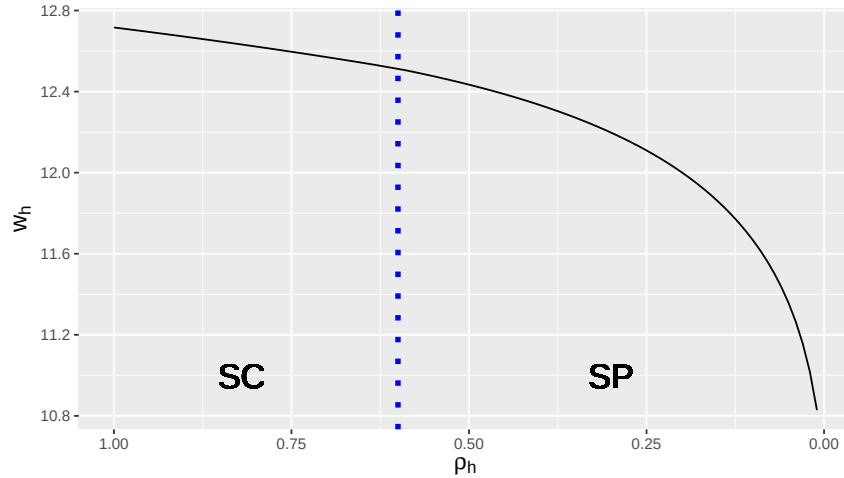


Figure 3.6: Changes in high-skilled wages w.r.t. high-skilled workers' flexibility

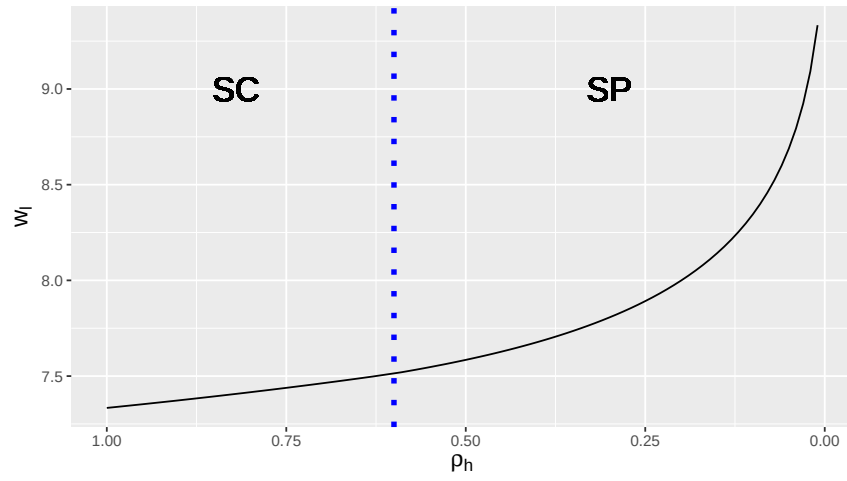


Figure 3.7: Changes in low-skilled wages w.r.t. high-skilled workers' flexibility

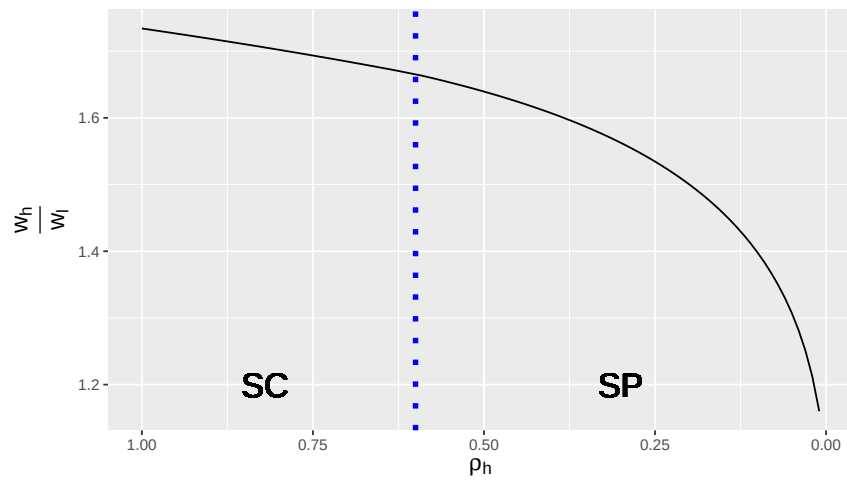


Figure 3.8: Changes in city-wide skill premium w.r.t. high-skilled workers' flexibility

3.5.5 Interpretations

My numerical examples convey a compelling narrative of how the workers’ spatial sorting pattern within a city and their wage structures are intricately linked to the flexibility of high-skilled jobs. When such jobs lack flexibility, high-skilled workers prioritize living near the city center to minimize commutes, leveraging their higher income to outcompete low-skilled workers for prime residential locations. This behaviour necessitates a wage structure that compensates for their proximity to work locations. The firm must offer high-skilled workers wages that not only reflect their skills but also the essentiality of shorter commutes.

Conversely, increased job flexibility (lower ρ_h) allows high-skilled workers to reduce their commuting costs. This shift reduces the wage premium firms need to offer to attract high-skilled workers to live and work in the city. As high-skilled jobs become sufficiently flexible, firms adjust their wage offerings downwards in response to the reduced need to compensate for commuting, and high-skilled workers are drawn to suburban areas. Low-skilled workers, still requiring higher wages for longer commutes, find themselves “displaced” to the city centre. This transition leads to an SP city pattern.

My model’s implications resonate with the growing trend towards remote work, suggesting that the ability to work from home incentivizes high-skilled workers to seek more affordable living spaces without sacrificing job quality (J. Brueckner et al., 2021). It underscores the endogenous nature of wages, which is influenced by the need to optimize the composition of the workforce to achieve profit-maximizing production. Essentially, as high-skilled workers relocate to optimize their living situations in response to variations to job flexibility, the supply and demand for both types of labour and their corresponding wages will change to maintain a balanced skill composition in the labour market. As a result, the equilibrium skill premium will be lower in cities with SP patterns compared to those with SC ones, as the flexibility of high-skilled jobs makes it relatively cheaper for firms to attract high-skilled workers.

My theory offers an explanation for numerous findings in the existing literature, thereby highlighting its real-life implications and ability to elucidate empirical evidence. For instance, J. Brueckner et al. (2021) confirm that working from home tends to diminish the price premium associated with good job access. This phenomenon is exemplified by the decreasing skill premium depicted in Figure 3.8, which demonstrates the lower skill premium in SP cities compared to SC ones. Similarly, Oettinger (2011) uncover a wage “penalty” for workers who are home-based, further supporting the notion that job flexibility and remote work can lead to shifts in wage structures. My model not only captures these empirical observations but also offers a framework to understand the underlying mechanisms that drive these changes in the urban labour market.

3.6 Conclusion

In this study, I extend the classic monocentric city model to incorporate an endogenous labour market and job flexibility. My model captures the urban dynamics in which commuting costs depend on both travel distance and time, leading to an endogenous spatial

sorting of heterogeneously skilled workers within the city. I propose to incorporate workplace flexibility, where high-skilled workers possess more job flexibility and autonomy compared to their low-skilled counterparts, resulting in lower commuting costs and influencing the spatial sorting patterns in a city.

Utilizing data from the 2016 Canadian Census, my model's implications align with much of the cross-city empirical evidence. The observed association between the spatial sorting pattern and the city-wide skill premium in the data supports my theory. My model predicts that SC cities, characterized by a concentration of high-skilled workers in the city centre, will exhibit higher wage premiums compared to the SP cities. These trends are identified in both the literature and my empirical analysis in Section 3.3.2. As per my model's implications, the heightened demand for centrally located housing by high-skilled workers elevates housing prices in SC cities, thereby compelling the employer to offer higher wages to retain these workers within the city. For SP cities, the model suggests these trends are reversed. It explores how wages, housing demands, and commuting costs interact to influence the location decisions of high- and low-skilled workers, thereby shaping the spatial distribution of talent and resources within a city. This approach not only captures the complexity of urban labour markets but also offers insights into how workplace flexibility and spatial allocation patterns directly impact wage disparities between worker groups.

There are several interesting directions for future research that could build upon the proposed model. One possible extension is to consider the model in the context of multiple cities, as large cities often give rise to smaller neighbouring cities. This extension could contribute to a broader understanding of cross-city interactions, complementing the insights provided by the current model. Another avenue for investigation is the integration of a time dimension into the model to assess the model's short-term and long-term economic outcomes. Developing a dynamic version of the model could provide additional insights into the transitions between equilibria with different sorting patterns over time.

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APPENDICES

Appendix A

List of U.S. Cities Included

Table A.1 displays the 68 metropolitan areas included in the study sample and their estimated working population in the year of 2012.

Table A.1: List of Included Metropolitan Areas

Metropolitan Area Name	Estimated Working Population in 2012
New York - Newark - Jersey City, NY-NJ-PA	4,652,833
Los Angeles - Long Beach-Anaheim, CA	2,937,674
Chicago - Naperville - Elgin, IL-IN-WI	2,277,191
Dallas - Fort Worth-Arlington, TX	1,739,288
Washington - Arlington - Alexandria, DC-VA-MD-WV	1,690,154
Houston - The Woodlands-Sugar Land, TX	1,498,560
Philadelphia - Camden - Wilmington, PA-NJ-DE-MD	1,302,521
Atlanta - Sandy Springs - Roswell, GA	1,290,037
San Francisco - Oakland - Hayward, CA	1,072,861
Seattle - Tacoma - Bellevue, WA	930,073
Phoenix - Mesa - Scottsdale, AZ	923,830
Minneapolis - St. Paul - Bloomington, MN-WI	889,876
Detroit - Warren - Dearborn, MI	874,785
San Diego - Carlsbad, CA	738,429
Riverside - San Bernardino - Ontario, CA	670,929
Baltimore - Columbia - Towson, MD	664,387
Miami - Fort Lauderdale - West Palm Beach, FL	658,184
St. Louis, MO-IL	637,619

Continued on next page

Table A.1 – continued from previous page

Metropolitan Area Name	Estimated Working Population in 2012
Tampa - St. Petersburg - Clearwater, FL	632,401
Orlando - Kissimmee - Sanford, FL	556,212
San Jose - Sunnyvale - Santa Clara, CA	550,892
Portland - Vancouver - Hillsboro, OR-WA	511,327
Columbus, OH	499,816
Las Vegas - Henderson - Paradise, NV	487,871
San Antonio - New Braunfels, TX	487,245
Cincinnati, OH-KY-IN	486,182
Austin - Round Rock, TX	482,932
Kansas City, MO-KS	482,472
Indianapolis - Carmel - Anderson, IN	475,560
Cleveland - Elyria, OH	472,780
Pittsburgh, PA	464,427
Sacramento - Roseville - Arden Arcade, CA	439,878
Virginia Beach - Norfolk - Newport News, VA-NC	411,923
Nashville Davidson - Murfreesboro - Franklin, TN	404,620
Milwaukee - Waukesha - West Allis, WI	399,708
Salt Lake City, UT	331,529
Hartford - West Hartford - East Hartford, CT	321,134
Oklahoma City, OK	300,193
New Orleans - Metairie, LA	296,826
Louisville / Jefferson County, KY-IN	295,882
Raleigh, NC	295,387
Memphis, TN-MS-AR	285,297
Richmond, VA	276,311
Jacksonville, FL	271,725
Buffalo - Cheektowaga - Niagara Falls, NY	258,636
Urban Honolulu, HI	242,065
Birmingham - Hoover, AL	240,788
Bridgeport - Stamford - Norwalk, CT	220,522
Albany - Schenectady - Troy, NY	215,730
Grand Rapids - Wyoming, MI	208,429
Rochester, NY	206,461
Albuquerque, NM	200,256

Continued on next page

Table A.1 – continued from previous page

Metropolitan Area Name	Estimated Working Population in 2012
Columbia, SC	197,706
Baton Rouge, LA	197,603
Tucson, AZ	197,427
Omaha - Council Bluffs, NE-IA	194,561
Greensboro - High Point, NC	188,402
Dayton, OH	183,930
Charleston - North Charleston, SC	179,336
Little Rock - North Little Rock - Conway, AR	178,802
Knoxville, TN	176,727
Allentown - Bethlehem - Easton, PA-NJ	169,429
New Haven - Milford, CT	167,827
Akron, OH	164,191
Greenville - Anderson - Mauldin, SC	163,576
Oxnard - Thousand Oaks - Ventura, CA	161,465
Harrisburg - Carlisle, PA	161,369
El Paso, TX	159,257

Appendix B

List of Job Requirements Included for Occupational Task Indices

Below are the tables that list all job requirements used to construct the occupational task indices.

Table B.1: Variables used to create non-routine analytical tasks

Variable ID	Variable name	Description
1.A.1.b.1	Fluency of ideas	The ability to come up with a number of ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity).
1.A.1.b.2	Originality	The ability to come up with unusual or clever ideas about a given topic or situation or to develop creative ways to solve a problem.
1.C.7.a	Innovation	Job requires creativity and alternative thinking to develop new ideas for and answers to work-related problems.
1.C.7.b	Analytical thinking	Job requires analyzing information and using logic to address work-related issues and problems.
2.A.2.a	Critical thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions, or approaches to problems.
2.A.2.b	Active learning	Understanding the implications of new information for both current and future problem-solving and decision-making.
2.B.2.Í	Complex problem solving	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.
2.B.4.e	Judgment and decision making	Considering the relative costs and benefits of potential actions to choose the most appropriate one.
4.A.2.a.3	Evaluating information to determine compliance	Using relevant information and individual judgment to determine whether events or processes comply with laws, regulations, or standards.
4.A.2.b.1	Making decisions and solving problems	Analyzing information and evaluating results to choose the best solution and solve problems.
4.A.2.b.2	Thinking creatively	Developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions.
4.A.2.b.4	Developing objectives and strategies	Establishing long-range objectives and specifying the strategies and actions to achieve them.

Table B.2: Variables used to create non-routine interactive tasks

Variable ID	Variable name	Description
1.C.2.b	Leadership	Job requires a willingness to lead, take charge, and offer opinions and direction.
2.A.2.d	Monitoring	Monitoring/assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action.
2.B.1.c	Persuasion	Persuading others to change their minds or behavior.
2.B.5.d	Management of personnel resources	Motivating, developing, and directing people as they work, identifying the best people for the job.
4.A.4.a.1	Interpreting the meaning of information for others	Translating or explaining what information means and how it can be used.
4.A.4.a.4	Establishing and maintaining interpersonal relationships	Developing constructive and cooperative working relationships with others and maintaining them over time.
4.A.4.b.1	Coordinating the work and activities of others	Getting members of a group to work together to accomplish tasks.
4.A.4.C.2	Staffing organizational units	Recruiting, interviewing, selecting, hiring, and promoting employees in an organization.

Table B.3: Variables used to create routine cognitive tasks

Variable ID	Variable name	Description
1.A.1.b.6	Information ordering	The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).
1.A.1.c.2	Number facility	The ability to add, subtract, multiply, or divide quickly and correctly.
1.A.1.d.1	Memorization	The ability to remember information such as words, numbers, pictures, and procedures.
2.A.1.e	Mathematics	Using mathematics to solve problems.

Table B.4: Variables used to create routine manual tasks

Variable ID	Variable name	Description
1.A.2.a.2	Manual dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
1.A.2.a.3	Finger dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
1.A.2.c.2	Wrist-finger speed	The ability to make fast, simple, repeated movements of the fingers, hands, and wrists.

Table B.5: Variables used to create non-routine manual tasks

Variable ID	Variable name	Description
1.A.2.b.2	Multi-limb coordination	The ability to coordinate two or more limbs (e.g., two arms, two legs, or one leg and one arm) while sitting, standing, or lying down.
1.A.2.b.4	Rate control	The ability to time your movements or the movement of a piece of equipment in anticipation of changes in the speed and/or direction of a moving object or scene.
4.A.3.a.1	Performing general physical activities	Performing physical activities that require considerable use of your arms and legs and moving your whole body, such as climbing, lifting, balancing, walking, stooping, and handling of materials.
4.A.3.a.3	Controlling machines and processes	Using either control mechanisms or direct physical activity to operate machines or processes (not including computers or vehicles).
2.B.3.1	Repairing	Repairing machines or systems using the needed tools.
1.A.2.b.1	Control precision	The ability to quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions.
4.A.3.a.4	Operating vehicles, mechanized devices, or equipment	Running, maneuvering, navigating, or driving vehicles or mechanized equipment, such as forklifts, passenger vehicles, aircraft, or watercraft.

Appendix C

Variable Description for the Study Sample

Table C.1 displays the variables contained in the study sample.

Table C.1: Variables Contained in the Study Sample

Variable	Nature	Levels
Survey Year	Categorical	2016
Person Weight	Continuous	N/A
Occupation Weight ¹	Continuous	N/A
State of Residence	Categorical	by state
City of Residence	Categorical	by city
Group Quarters Status	Categorical	households
Housing Ownership	Categorical	own/rent
Housing Value ²	Continuous	N/A
Number of Children	Continuous	N/A
Gender	Categorical	male/female
Age	Continuous	N/A
Marital Status	Categorical	married/single
Racial Group	Categorical	Caucasian/African American/Native/Chinese/ Japanese/Other Asian/Others/Mixed Races
Education Attainment	Categorical	less than high-school/high-school/associate/ bachelor/graduate
Class of Worker	Categorical	private/public
Employment Status	Categorical	employed/unemployed/not in labour force
Industry	Categorical	by industry
Occupation	Categorical	by occupation
Task Indices	Continuous	N/A
Weeks Worked Last Year	Continuous	N/A
Usual Hours Worked	Continuous	N/A
Wages ³	Continuous	N/A
Place of Work	Categorical	by metropolitan area
Work from Home	Categorical	yes/no
Commuting Time ⁴	Continuous	N/A

¹ The occupation weights are generalized based on the 2012 population.

² The housing values are adjusted to the 1999 level.

³ Wages are adjusted to the 1999 level.

⁴ The commuting time is converted into two-way in hours.

Appendix D

Regression Estimates for Base Models and Model with Intersections

Table D.1 displays the estimated results for all important variables regarding the four base models and the model with interaction term between commuting time and gender.

Table D.1: Base/Interaction Model Estimates

	(1)	(2)	(3)	(4)	(5)
Commuting Time	0.093*** (0.016)	0.06*** (0.011)	0.033*** (0.01)	0.015** (0.01)	0.004 (0.01)
Private Sector			-0.102*** (0.01)	-0.024*** (0.01)	-0.024*** (0.01)
Female				-0.118*** (0.004)	-0.141*** (0.005)
Age				0.056*** (0.002)	0.056*** (0.002)
Married				0.125*** (0.003)	0.125*** (0.003)
African American				-0.106*** (0.005)	-0.107*** (0.005)
Less than High-School				-0.141*** (0.01)	-0.141*** (0.01)
Associate Degrees				0.085*** (0.003)	0.085*** (0.003)
Bachelor's				0.304*** (0.006)	0.304*** (0.006)
Graduate				0.49*** (0.007)	0.49*** (0.007)
Children under 14				0.057*** (0.003)	0.057*** (0.003)
Female $\times$ Married				-0.098*** (0.004)	-0.099*** (0.004)
Female $\times$ Children under 14				0.004 (0.003)	0.003 (0.003)
Female $\times$ Commuting					0.025*** (0.004)
NRA Index				0.086*** (0.003)	0.086*** (0.003)
NRI Index				-0.058*** (0.004)	-0.058*** (0.004)
NRM Index				0.009*** (0.001)	0.009*** (0.001)
RM Index				-0.061*** (0.002)	0.086*** (0.002)
RC Index				0.069*** (0.004)	0.069*** (0.004)
Year FE	Y	Y	Y	Y	Y
City FE	N	Y	Y	Y	Y
Industry FE	N	N	Y	Y	Y
Age ²	N	N	N	Y	Y
Race FE	N	N	N	Y	Y
R ²	0.01	0.01	0.2	0.48	0.48

¹ *p<0.1; **p<0.05; ***p<0.01² Data Source: ACS 2012-2017; 68 cities.³ All regressions are estimated using OLS with clustered standard errors regarding working places.

Appendix E

Regression Estimates for Male-Specific Model

Table E.1 displays the estimated results for all important variables regarding the model of male sub-samples.

Table E.1: Male Sub-Sample Estimations

	Estimation
CT	-0.007
CT $\times$ Private Sector	0.02***
CT $\times$ IND: Newspaper Publishing/Printing	0.073***
CT $\times$ IND: Department Stores	0.066***
CT $\times$ Age	0.0003**
CT $\times$ Married	0.009**
CT $\times$ Less than High-School	-0.013**
CT $\times$ Associates	-0.004**
CT $\times$ Bachelor's	-0.019***
CT $\times$ Graduate Degrees	-0.013**
CT $\times$ Children $\leq$ 14 Years Old	0.008*
NRA Index	0.082***
NRI Index	-0.061***
NRM Index	0.004***
RM Index	-0.108***
RC Index	0.079***
Year FE	Y
City FE	Y
Industry FE	Y
Age ²	Y
Race FE	Y

¹ *p<0.1; **p<0.05; ***p<0.01

² Data Source: ACS 2012-2017; 68 cities; male only

³ Commuting time is interacted with class of worker, industry, age, marital status, education attainment and whether the individual has children less than or equal to 14 years old.

⁴ The regression is estimated using OLS with clustered standard errors regarding working places.

⁵ Only the industries that have positive and significant interaction coefficients are displayed here.

Appendix F

Quantile Regression Estimates

The model estimates of the quantile regressions without and with the interaction term are displayed in Table F.1 and F.2 respectively.

Table F.1: Quantile Regression Estimates - Without Interaction

	0.1	0.25	0.5	0.75	0.9
Commuting Time	0.033*** (0.001)	0.027*** (0.001)	0.019*** (0.001)	0.009*** (0.001)	-0.005*** (0.001)
Private Sector	-0.096*** (0.003)	-0.07*** (0.002)	-0.033*** (0.002)	0.004 (0.003)	0.04*** (0.004)
Female	-0.054*** (0.003)	-0.077*** (0.002)	-0.107*** (0.002)	-0.14*** (0.002)	-0.187*** (0.003)
Age	0.04*** (0.00)	0.047*** (0.00)	0.055*** (0.00)	0.059*** (0.00)	0.063*** (0.00)
Married	0.142*** (0.003)	0.133*** (0.002)	0.119*** (0.002)	0.107*** (0.002)	0.103*** (0.003)
African American	-0.095*** (0.003)	-0.098*** (0.002)	-0.099*** (0.002)	-0.098*** (0.002)	-0.096*** (0.003)
Less than High-School	-0.116*** (0.003)	-0.145*** (0.003)	-0.159*** (0.003)	-0.159*** (0.003)	-0.143*** (0.004)
Associate Degrees	0.07*** (0.002)	0.083*** (0.002)	0.093*** (0.002)	0.095*** (0.002)	0.084*** (0.002)
Bachelor's	0.23*** (0.002)	0.27*** (0.002)	0.3*** (0.002)	0.33*** (0.002)	0.34*** (0.003)
Graduate	0.39*** (0.003)	0.45*** (0.002)	0.49*** (0.002)	0.52*** (0.002)	0.57*** (0.004)
Children under 14	0.049*** (0.002)	0.053*** (0.002)	0.051*** (0.002)	0.053*** (0.002)	0.068*** (0.003)
Female $\times$ Married	-0.11*** (0.003)	-0.103*** (0.003)	-0.093*** (0.002)	-0.082*** (0.003)	-0.084*** (0.004)
Female $\times$ Children under 14	-0.006** (0.003)	0.001 (0.002)	0.01*** (0.002)	0.005* (0.002)	-0.008** (0.004)
NRA Index	0.080*** (0.002)	0.090*** (0.001)	0.092*** (0.001)	0.087*** (0.001)	0.077*** (0.002)
NRI Index	-0.036*** (0.003)	-0.037*** (0.002)	-0.043*** (0.002)	-0.060*** (0.002)	-0.088*** (0.003)
NRM Index	0.010*** (0.001)	0.006*** (0.001)	0.004*** (0.001)	0.008*** (0.001)	0.022*** (0.001)
RM Index	-0.004 (0.003)	-0.020*** (0.002)	-0.044*** (0.002)	-0.076*** (0.003)	-0.114*** (0.004)
RC Index	0.078*** (0.003)	0.071*** (0.003)	0.061*** (0.002)	0.053*** (0.003)	0.052*** (0.004)
Year FE	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Age ²	Y	Y	Y	Y	Y
Race FE	Y	Y	Y	Y	Y

¹ *p<0.1; **p<0.05; ***p<0.01² Data Source: ACS 2012-2017; 68 cities.

Table F.2: Quantile Regression Estimates - With Interaction

	0.1	0.25	0.5	0.75	0.9
Commuting Time	0.025*** (0.002)	0.016*** (0.001)	0.007*** (0.001)	-0.002 (0.001)	-0.016*** (0.002)
Private Sector	-0.097*** (0.003)	-0.07*** (0.002)	-0.033*** (0.002)	0.005* (0.003)	0.04*** (0.004)
Female	-0.072*** (0.004)	-0.102*** (0.003)	-0.134*** (0.002)	-0.162*** (0.003)	-0.21*** (0.004)
Age	0.04*** (0.001)	0.047*** (0.001)	0.055*** (0.001)	0.059*** (0.001)	0.063*** (0.001)
Married	0.143*** (0.003)	0.134*** (0.002)	0.12*** (0.002)	0.108*** (0.002)	0.103*** (0.003)
African American	-0.097*** (0.003)	-0.099*** (0.002)	-0.01*** (0.002)	-0.098*** (0.002)	-0.096*** (0.003)
Less than High-School	-0.116*** (0.003)	-0.145*** (0.003)	-0.158*** (0.003)	-0.159*** (0.003)	-0.143*** (0.005)
Associate Degrees	0.07*** (0.002)	0.082*** (0.002)	0.093*** (0.002)	0.095*** (0.002)	0.083*** (0.002)
Bachelor's	0.23*** (0.002)	0.27*** (0.002)	0.31*** (0.002)	0.33*** (0.002)	0.34*** (0.003)
Graduate	0.39*** (0.003)	0.45*** (0.002)	0.49*** (0.002)	0.52*** (0.002)	0.57*** (0.004)
Children under 14	0.049*** (0.002)	0.053*** (0.002)	0.051*** (0.002)	0.054*** (0.002)	0.069*** (0.003)
Female $\times$ Married	-0.11*** (0.003)	-0.103*** (0.003)	-0.093*** (0.002)	-0.083*** (0.003)	-0.085*** (0.004)
Female $\times$ Children under 14	-0.006* (0.003)	0.002 (0.002)	0.01*** (0.002)	0.004 (0.002)	-0.009** (0.004)
Female $\times$ Commuting	0.019*** (0.002)	0.026*** (0.002)	0.028*** (0.002)	0.023*** (0.002)	0.025*** (0.003)
NRA Index	0.080*** (0.002)	0.090*** (0.001)	0.093*** (0.001)	0.087*** (0.001)	0.077*** (0.002)
NRI Index	-0.036*** (0.003)	-0.037*** (0.002)	-0.043*** (0.002)	-0.059*** (0.002)	-0.088*** (0.003)
NRM Index	0.010*** (0.001)	0.006*** (0.001)	0.004*** (0.001)	0.008*** (0.001)	0.022*** (0.001)
RM Index	-0.004 (0.003)	-0.021*** (0.002)	-0.044*** (0.002)	-0.076*** (0.003)	-0.114*** (0.004)
RC Index	0.079*** (0.003)	0.072*** (0.003)	0.060*** (0.002)	0.053*** (0.003)	0.052*** (0.004)
Year FE	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Age ²	Y	Y	Y	Y	Y
Race FE	Y	Y	Y	Y	Y

¹ *p<0.1; **p<0.05; ***p<0.01² Data Source: ACS 2012-2017; 68 cities.

Appendix G

Variable Description for Study Sample

Table G.1 displays the variables contained in the study sample.

Table G.1: Variables Contained in the Study Sample

Variable	Nature	Levels
Person Weight	Continuous	N/A
Occupation Weight ¹	Continuous	N/A
Group Quarters Status	Categorical	households
Housing Ownership	Categorical	own/rent
Number of Children	Continuous	N/A
Gender	Categorical	male/female
Age	Continuous	N/A
Marital Status	Categorical	married/single
Racial Group	Categorical	Caucasian/African American/Native/Chinese/ Japanese/Other Asian/Others/Mixed Races
Education Attainment	Categorical	less than high-school/high-school/associate/ bachelor/graduate
Employment Status	Categorical	employed/unemployed/not in labour force
Industry	Categorical	by industry
Occupation	Categorical	by occupation
Task Indices	Continuous	N/A
Weeks Worked Last Year	Continuous	N/A
Usual Hours Worked	Continuous	N/A
Wages	Continuous	N/A
Place of Work	Categorical	by metropolitan area
State of Workplace	Categorical	by state
Work from Home	Categorical	yes/no
Commuting Time ¹	Continuous	N/A
Normalized Cohesion Index	Continuous	N/A
Average Node Degree	Continuous	N/A
Self-loop Proportion	Continuous	N/A

¹ The commuting time is converted into two-way in hours.

Appendix H

OLS Regressions

Table H.1 displays the full OLS models used in Section 2.4.1.

Table H.1: OLS Regression Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Commuting Time	0.028*** (0.01)	0.058*** (0.003)	0.029*** (0.006)	0.067*** (0.004)	0.018*** (0.007)	0.031*** (0.01)
Married	0.146*** (0.005)	0.054*** (0.004)				
Age	0.054*** (0.005)	0.052*** (0.002)	0.061*** (0.003)	0.047*** (0.002)	0.049*** (0.004)	0.053*** (0.003)
African American	-0.143*** (0.01)	-0.06*** (0.007)	-0.169*** (0.01)	-0.065*** (0.008)	-0.088*** (0.01)	-0.05*** (0.01)
High-School Diploma	0.175*** (0.01)	0.13*** (0.01)	0.193*** (0.01)	0.13*** (0.01)	0.089*** (0.02)	0.11*** (0.02)
Associate Degrees	0.252*** (0.01)	0.24*** (0.01)	0.28*** (0.01)	0.24*** (0.01)	0.145*** (0.02)	0.2*** (0.02)
Bachelor's	0.491*** (0.02)	0.46*** (0.02)	0.53*** (0.02)	0.47*** (0.02)	0.339*** (0.02)	0.39*** (0.02)
Graduate	0.691*** (0.02)	0.63*** (0.02)	0.73*** (0.02)	0.65*** (0.02)	0.523*** (0.02)	0.54*** (0.02)
Number of Children	0.018*** (0.002)	-0.011*** (0.002)	0.017*** (0.002)	-0.01*** (0.002)	0.011* (0.006)	-0.02*** (0.004)
Children under 14	0.043*** (0.005)	0.09*** (0.005)	0.042*** (0.005)	0.093*** (0.006)	0.054*** (0.016)	0.035*** (0.01)
NRA Index	0.081*** (0.005)	0.032*** (0.007)	0.086*** (0.006)	0.036*** (0.007)	0.066*** (0.008)	0.024*** (0.012)
NRI Index	-0.085*** (0.008)	-0.002 (0.007)	-0.072*** (0.009)	0.019* (0.007)	-0.150*** (0.013)	-0.066*** (0.014)
NRM Index	-0.001 (0.003)	-0.023*** (0.003)	-0.005 (0.003)	-0.028*** (0.003)	0.019*** (0.004)	-0.008 (0.005)
RM Index	0.094*** (0.011)	-0.027*** (0.007)	0.104*** (0.012)	-0.035*** (0.007)	0.060*** (0.018)	-0.009 (0.012)
RC Index	0.115*** (0.011)	0.110*** (0.009)	0.104*** (0.013)	0.094*** (0.008)	0.160*** (0.014)	0.153*** (0.018)
Sample	All Male	All Female	Married Male	Married Female	Single Male	Single Female
Age ²	Y	Y	Y	Y	Y	Y
State/Industry/Race FE	Y	Y	Y	Y	Y	Y

¹ *p<0.1; **p<0.05; ***p<0.01² Data Source: ACS 2016.³ All regressions are estimated using OLS with clustered standard errors regarding working places.

Appendix I

2SLS Regressions

Table I.1 displays the full 2SLS model with IV normalized cohesion index as the instrument. Since the average node degree and the self-loop proportion are not strong instruments, the estimates are less informative and the models are omitted.

Table I.1: 2SLS Regression Estimates - Normalized Cohesion

	(1)	(2)	(3)	(4)	(5)	(6)
Commuting Time	0.64*** (0.11)	0.64*** (0.1)	0.66*** (0.11)	0.74*** (0.12)	0.58*** (0.12)	0.43*** (0.09)
Married	0.116*** (0.008)	0.059*** (0.007)				
Age	0.052*** (0.002)	0.052*** (0.002)	0.058*** (0.003)	0.048*** (0.002)	0.048*** (0.004)	0.053*** (0.003)
African American	-0.175*** (0.01)	-0.113*** (0.02)	-0.194*** (0.02)	-0.123*** (0.02)	-0.134*** (0.02)	-0.09*** (0.01)
High-School Diploma	0.17*** (0.01)	0.12*** (0.01)	0.18*** (0.01)	0.12*** (0.02)	0.11*** (0.02)	0.1*** (0.02)
Associate Degrees	0.24*** (0.01)	0.21*** (0.01)	0.26*** (0.01)	0.21*** (0.02)	0.17*** (0.02)	0.18*** (0.02)
Bachelor's	0.48*** (0.02)	0.42*** (0.02)	0.52*** (0.02)	0.44*** (0.02)	0.35*** (0.02)	0.35*** (0.02)
Graduate	0.69*** (0.02)	0.6*** (0.02)	0.72*** (0.02)	0.62*** (0.02)	0.54*** (0.03)	0.51*** (0.02)
Number of Children	0.016*** (0.002)	-0.002 (0.003)	0.015*** (0.002)	0.002 (0.003)	0.013 (0.009)	-0.018*** (0.005)
Children under 14	0.039*** (0.006)	0.08*** (0.006)	0.037*** (0.006)	0.079*** (0.008)	0.036*** (0.018)	0.024** (0.01)
NRA Index	0.075*** (0.005)	0.037*** (0.008)	0.078*** (0.006)	0.044*** (0.008)	0.067*** (0.011)	0.025** (0.012)
NRI Index	-0.065*** (0.008)	-0.025*** (0.007)	-0.055*** (0.009)	-0.003 (0.009)	-0.118*** (0.013)	-0.088*** (0.012)
NRM Index	-0.005* (0.003)	-0.010*** (0.003)	-0.007*** (0.003)	-0.158*** (0.004)	0.011** (0.005)	0.004 (0.005)
RM Index	0.118*** (0.010)	-0.004 (0.008)	0.138*** (0.011)	-0.143 (0.009)	0.056*** (0.017)	0.015 (0.014)
RC Index	0.101*** (0.010)	0.112*** (0.009)	0.096*** (0.012)	0.087*** (0.010)	0.128*** (0.017)	0.166*** (0.016)
Sample	All Male	All Female	Married Male	Married Female	Single Male	Single Female
Age ²	Y	Y	Y	Y	Y	Y
State/Industry/Race FE	Y	Y	Y	Y	Y	Y

¹ *p<0.1; **p<0.05; ***p<0.01² Data Source: ACS 2016.³ All regressions are estimated using 2SLS with clustered standard errors regarding working places.

Appendix J

2SLS Regressions in the Discussion Sections

Table J.1 displays the 2SLS results for married male and female, separated by their parental status. Table J.2 illustrates the sensitivity analysis where I include single individuals in my sample and control for marital status. The pooled sample is also separated by parental statuses.

Table J.3 displays the 2SLS model using the management occupation sub-sample and the normalized cohesion index as the instrument.

Table J.1: IV Estimates - Parental Status

	(1)	(2)	(3)	(4)
Commuting Time	0.78*** (0.17)	0.62*** (0.10)	0.71*** (0.13)	0.76*** (0.14)
Age	0.046*** (0.004)	0.066*** (0.003)	0.04*** (0.004)	0.06*** (0.003)
African American	-0.179*** (0.025)	-0.198*** (0.02)	-0.125*** (0.02)	-0.121*** (0.02)
High-School Diploma	0.019*** (0.024)	0.177*** (0.02)	0.11*** (0.02)	0.12*** (0.02)
Associate Degrees	0.25*** (0.025)	0.263*** (0.016)	0.20*** (0.021)	0.22*** (0.022)
Bachelor's	0.50*** (0.03)	0.52*** (0.02)	0.42*** (0.02)	0.45*** (0.02)
Graduate	0.70*** (0.03)	0.73*** (0.02)	0.57*** (0.03)	0.64*** (0.02)
Number of Children		0.014*** (0.003)		0.016*** (0.004)
Children under 14		0.025*** (0.01)		0.103*** (0.01)
Sample	Married Male, No Children	Married Male, With Children	Married Female, No Children	Married Female, With Children
Age ²	Y	Y	Y	Y
State/Industry/Race FE	Y	Y	Y	Y
Task Requirements	Y	Y	Y	Y

¹ *p<0.1; **p<0.05; ***p<0.01² Data Source: ACS 2016, married individuals only.³ All regressions are estimated using 2SLS with clustered standard errors regarding working places.

Table J.2: IV Estimates - Parental Status, Pooled Sample

	(1)	(2)	(3)	(4)
Commuting Time	0.71*** (0.14)	0.60*** (0.1)	0.56*** (0.09)	0.71*** (0.13)
Married	0.117*** (0.01)	0.089*** (0.02)	0.051*** (0.01)	0.084*** (0.01)
Age	0.042*** (0.003)	0.063*** (0.003)	0.050*** (0.003)	0.058*** (0.003)
African American	-0.160*** (0.016)	-0.192*** (0.016)	-0.116*** (0.013)	-0.106*** (0.02)
High-School Diploma	0.16*** (0.01)	0.17*** (0.09)	0.12*** (0.02)	0.11*** (0.02)
Associate Degrees	0.22*** (0.02)	0.26*** (0.01)	0.21*** (0.02)	0.20*** (0.02)
Bachelor's	0.43*** (0.02)	0.51*** (0.02)	0.41*** (0.02)	0.43*** (0.02)
Graduate	0.63*** (0.02)	0.72*** (0.02)	0.57*** (0.02)	0.62*** (0.02)
Number of Children		0.014*** (0.003)		0.014*** (0.004)
Children under 14		0.024*** (0.007)		0.098*** (0.009)
Sample	Male, No Children	Male, With Children	Female, No Children	Female, With Children
Age ²	Y	Y	Y	Y
State/Industry/Race FE	Y	Y	Y	Y
Task Requirements	Y	Y	Y	Y

¹ *p<0.1; **p<0.05; ***p<0.01

² Data Source: ACS 2016.

³ All regressions are estimated using 2SLS with normalized cohesion index as the IV; standard errors are clustered regarding working places.

Table J.3: IV Estimates - Management Occupation Sub-Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Commuting Time	0.68*** (0.12)	0.71*** (0.11)	0.72*** (0.11)	0.87*** (0.16)	0.47*** (0.11)	0.36*** (0.14)
Married	0.116*** (0.019)	0.058*** (0.02)				
Age	0.073*** (0.005)	0.071*** (0.005)	0.077*** (0.005)	0.06*** (0.01)	0.075*** (0.01)	0.08*** (0.01)
African American	-0.245*** (0.025)	-0.171*** (0.03)	-0.25*** (0.03)	-0.184*** (0.03)	-0.22*** (0.05)	-0.15*** (0.04)
High-School Diploma	0.065* (0.04)	-0.049 (0.09)	0.07 (0.04)	-0.12 (0.10)	0.05 (0.08)	0.097 (0.1)
Associate Degrees	0.19*** (0.05)	0.058 (0.084)	0.19*** (0.05)	-0.001 (0.10)	0.16* (0.09)	0.18* (0.1)
Bachelor's	0.50*** (0.05)	0.33*** (0.09)	0.51*** (0.05)	0.27*** (0.10)	0.41*** (0.09)	0.43*** (0.1)
Graduate	0.63*** (0.05)	0.47*** (0.09)	0.65*** (0.05)	0.41*** (0.10)	0.52*** (0.09)	0.53*** (0.1)
Number of Children	0.013** (0.005)	-0.007 (0.01)	0.011** (0.005)	-0.001 (0.01)	0.01 (0.03)	-0.037* (0.02)
Children under 14	0.038** (0.015)	0.103*** (0.015)	0.04*** (0.02)	0.095*** (0.02)	0.07 (0.03)	0.06 (0.04)
Sample	All Male	All Female	Married Male	Married Female	Single Male	Single Female
Age ²	Y	Y	Y	Y	Y	Y
State/Industry/Race FE	Y	Y	Y	Y	Y	Y
Task Requirements	Y	Y	Y	Y	Y	Y

¹ *p<0.1; **p<0.05; ***p<0.01² Data Source: ACS 2016, management occupations only.³ All regressions are estimated using 2SLS with clustered standard errors regarding working places.

Appendix K

List of Canadian CMAs and City Groups

Table K.1: City List Ranked by Distance Ratio

CMA Name	Distance Ratio	Distance Group
Edmonton	0.815	SC
Moncton	0.848	SC
Saguenay	0.879	SC
Montréal	0.889	SC
Toronto	0.897	SC
Calgary	0.899	SC
Regina	0.901	SC
Québec	0.904	SC
Ottawa-Gatineau	0.921	SC
Halifax	0.961	SC
Winnipeg	0.967	SC
Saskatoon	0.975	SC
Vancouver	0.989	SC
Hamilton	1.01	SP
Thunder Bay	1.016	SP
Windsor	1.03	SP
Victoria	1.061	SP
Barrie	1.063	SP
Sherbrooke	1.065	SP
St. John's	1.082	SP
Trois-Rivières	1.101	SP
Peterborough	1.119	SP
Lethbridge	1.133	SP
Kelowna	1.136	SP
Oshawa	1.139	SP
Abbotsford-Mission	1.176	SP
Guelph	1.186	SP
Kitchener-Cambridge-Waterloo	1.189	SP
Belleville	1.205	SP
Kingston	1.241	SP
London	1.259	SP
Saint John	1.323	SP
St.Catharines-Niagara	1.361	SP
Brantford	1.452	SP
Greater Sudbury	1.488	SP

Appendix L

Equilibrium Solution Details

By Equations 3.4.1.1, 3.4.1.3 and 3.4.3.2,

$$s_i^*(x) = \begin{cases} \frac{1}{\exp\{w_i - (tx + \rho_i w_i x) - \bar{V}_i\}} & \text{if } P_i \geq P_{-i} \\ 0 & \text{o.w.} \end{cases} \quad (\text{L.0.0.1})$$

$$c_i^*(x) = \begin{cases} w_i - (tx + \rho_i w_i x) - 1 & \text{if } P_i \geq P_{-i} \\ 0 & \text{o.w.} \end{cases}$$

Hence, by the definition of the population density (equation (3.4.5.1)),

$$D(x) = \phi(x) \exp\{w_l - (tx + \rho_l w_l x) - \bar{V}_l\} + (1 - \phi(x)) \exp\{w_h - (tx + \rho_h w_h x) - \bar{V}_h\}$$

Equilibrium 1: when $\frac{w_l}{w_h} < \rho_h$, the model yields the SC pattern equilibrium.

Based on the labour market clearing condition 3.4.5.3 and the solution of X (equation (3.4.6.2)):

$$\begin{aligned} L^* &= \int_{x=0}^{\frac{w_l-1}{t+\rho_l w_l}} \phi(x) \exp\{w_l - (tx + \rho_l w_l x) - \bar{V}_l\} dx \\ H^* &= \int_{x=0}^{\frac{w_l-1}{t+\rho_l w_l}} (1 - \phi(x)) \exp\{w_h - (tx + \rho_h w_h x) - \bar{V}_h\} dx \end{aligned} \quad (\text{L.0.0.2})$$

It follows that by the spatial allocation condition (3.5.1.3):

$$\begin{aligned}
L^* &= \int_{x_m}^{\frac{w_l-1}{t+\rho_l w_l}} \exp \left\{ w_l - (tx + \rho_l w_l x) - \bar{V}_l \right\} dx \\
&= \frac{1}{t + \rho_l w_l} \cdot \exp \left\{ w_l - (tx + \rho_l w_l x) - \bar{V}_l \right\} \Big|_{\frac{w_l-1}{t+\rho_l w_l}}^{x_m} \\
&= \frac{1}{t + \rho_l w_l} \cdot \left(\exp \left\{ w_l - \bar{V}_l - \frac{(\Delta w - \Delta \bar{V})(t + \rho_l w_l)}{\Delta \rho w} \right\} - \exp \left\{ 1 - \bar{V}_l \right\} \right) \\
H^* &= \int_{x=0}^{x_m} \exp \left\{ w_h - (tx + \rho_h w_h x) - \bar{V}_h \right\} dx \\
&= \frac{1}{t + \rho_h w_h} \cdot \exp \left\{ w_h - (tx + \rho_h w_h x) - \bar{V}_h \right\} \Big|_{x_m}^0 \\
&= \frac{1}{t + \rho_h w_h} \cdot \left(\exp \left\{ w_h - \bar{V}_h \right\} - \exp \left\{ w_h - \bar{V}_h - \frac{(\Delta w - \Delta \bar{V})(t + \rho_h w_h)}{\Delta \rho w} \right\} \right)
\end{aligned} \tag{L.0.0.3}$$

Note that $L^* > 0$ is guaranteed by the case condition. Equations (L.0.0.3) and (3.4.2.1) jointly determine w_l^* and w_h^* , L^* and H^* as functions of A, β, t, ρ_i and $\bar{V}_i$.

Equilibrium 2: when $\frac{w_l}{w_h} > \rho_h$, the model yields the SP pattern equilibrium.

Based on the labour market clearing condition 3.4.5.3 and the solution of X (equation (3.4.6.2)):

$$\begin{aligned}
L^* &= \int_{x=0}^{\frac{w_h-1}{t+\rho_h w_h}} \phi(x) \exp \left\{ w_l - (tx + \rho_l w_l x) - \bar{V}_l \right\} dx \\
H^* &= \int_{x=0}^{\frac{w_h-1}{t+\rho_h w_h}} (1 - \phi(x)) \exp \left\{ w_h - (tx + \rho_h w_h x) - \bar{V}_h \right\} dx
\end{aligned} \tag{L.0.0.4}$$

It follows that by the spatial allocation condition 3.5.1.5:

$$\begin{aligned}
L^* &= \int_0^{x_m} \exp \left\{ w_l - (tx + \rho_l w_l x) - \bar{V}_l \right\} dx \\
&= \frac{1}{t + \rho_l w_l} \cdot \exp \left\{ w_l - (tx + \rho_l w_l x) - \bar{V}_l \right\} \Big|_{x_m}^0 \\
&= \frac{1}{t + \rho_l w_l} \cdot \left(\exp \left\{ w_l - \bar{V}_l \right\} - \exp \left\{ w_l - \bar{V}_l - \frac{(\Delta w - \Delta \bar{V})(t + \rho_l w_l)}{\Delta \rho w} \right\} \right) \\
H^* &= \int_{x_m}^{\frac{w_h - 1}{t + \rho_h w_h}} \exp \left\{ w_h - (tx + \rho_h w_h x) - \bar{V}_h \right\} dx \\
&= \frac{1}{t + \rho_h w_h} \cdot \exp \left\{ w_h - (tx + \rho_h w_h x) - \bar{V}_h \right\} \Big|_{\frac{w_h - 1}{t + \rho_h w_h}}^{x_m} \\
&= \frac{1}{t + \rho_h w_h} \cdot \left(\exp \left\{ w_h - \bar{V}_h - \frac{(\Delta w - \Delta \bar{V})(t + \rho_h w_h)}{\Delta \rho w} \right\} - \exp \left\{ 1 - \bar{V}_h \right\} \right)
\end{aligned} \tag{L.0.0.5}$$

Note that $H^* > 0$ is guaranteed by the case condition. Equations (L.0.0.5) and (3.4.2.1) jointly determine w_l^* and w_h^* , L^* and H^* as functions of A, β, t, ρ_i and $\bar{V}_i$.