Household Search, Wages and Commuting Time
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Abstract

This paper examines the relationship between household employment status, commuting time, and wage dynamics, focusing on gender-specific labor market outcomes. Using a household search model, we analyze how the employment status of household members influences their marginal willingness to pay (MWP) for a reduced commuting time. We use data from Chile, a country with notably high commuting times and high gender wage gaps among OECD countries, to estimate our model.

We find that women exhibit a higher sensitivity to commuting time than men, highlighting the greater importance they place on non-market activities and caregiving responsibilities. The analysis reveals that both men's and women's MWP for reduced commuting time increases with their own and their spouse's wages. This suggests that a higher household income allows individuals to prioritize shorter commutes, potentially improving overall job satisfaction and work-life balance. Our findings have important implications for labor economics, particularly in designing policies that consider the complex interplay between household decision-making processes, commuting time, and gender-specific labor market behaviors.

Keywords: household search, commuting time, gender wage gap, labor market dynamics
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1 Introduction

Despite significant progress over the years, women continue to be underrepresented in high-earning jobs. Research by Bertrand (2018) highlights the preference among women for workplace flexibility, flexible working hours, proximity to home, or remote work, which can influence their career trajectories and earnings potential. Among the various job attributes, one aspect that has received limited attention as a contributor to gender wage gaps is the strong preference for shorter commutes. Clark et al. (2020) notes that commuting time is a significant factor for job satisfaction and subjective well-being. Petrongolo and Ronchi (2020) finds a positive and robust relationship between commuting time and wages, indicating that longer commutes may be compensated by higher wages, a trade-off that warrants further exploration. Moreover, household-level decisions, rather than individual-level decisions, play a significant role in shaping an individual's job search. Flabbi and Mabli (2018) points out that the employment status and caregiving responsibilities of household members can impact when, where, and how a person looks for employment. Understanding these dynamics is crucial for labor economics, particularly in dual-earner households, where coordination and shared responsibilities influence individual choices.

This paper investigates the relationship between these factors, focusing on how they affect the labor market outcomes for both men and women. In particular, we study how household members' employment status and caregiving duties influence their own and other members' marginal willingness to pay for reduced commuting time. This study is particularly relevant given the growing importance of dual-income households and the need for policies that consider gender-specific labor market behavior.

To explore these questions, we develop a household search model for workers strongly attached to the labor market, where a job is characterized by two attributes: wage and commuting time. In the model, the decisions of accepting and continuing in a job are endogenous. We structurally estimate the model using data from Chile, a country with one of the highest commuting times among OECD countries (60 mins/day vs. 35 mins/day). Chile presents an interesting case study because of its unique labor market characteristics, including a significant gender wage gap and varying commuting patterns between men and women. By leveraging detailed household survey data, we provide robust estimates of the parameters driving job search and acceptance decisions.

Our paper contribution is twofold. First, estimating the MWP is challenging; it is not trivial to consistently estimate the willingness to pay for job attributes using hedonic wage models when there are informational frictions in the labor market (van Ommeren, 2000b). Quantifying marginal willingness to pay (MWP) for reduced commuting time by gender allows us to monetize how much wage a woman/man is willing to sacrifice. Second, our study employs a dynamic search model that accounts for the household's joint decision-making process. By incorporating gender-specific job offer arrival rates and commuting times, we aim to capture the complexities faced by dual-earner households. While the theoretical significance of considering the household as the decision-making unit is gaining acceptance, there is limited knowledge of its empirical impact on labor market outcomes (Dey and Flinn, 2008).

The results of our analysis reveal significant gender differences in job search behavior and the valuation of commuting time. We find that women are generally more sensitive to commuting time than men, which has important implications for policies aimed at improving labor market outcomes for women. Our MWP estimates suggest that the trade-offs between wages and commuting time vary substantially across different household types. MWP for both men and women increases with their wages and their spouse's wages, suggesting that higher household income allows individuals to prioritize shorter commutes, potentially improving overall job satisfaction and work-life balance. We find significant gender differences in job search behavior and the valuation of commuting time, highlighting the need for tailored policy interventions.

Overall, this paper contributes to the literature on labor economics by providing a comprehensive analysis of the interactions between household employment search, wages, and commuting time. It builds on a rich literature examining household job search (Dey and Flinn, 2008; Guler et al., 2012; Mankart and Oikonomou, 2017; Flabbi and Mabli, 2018; García-Pérez and Rendon, 2020; Flinn et al., 2023; Pilossoph and Wee, 2021; Salazar-Saez, 2023). Our contribution lies in incorporating commuting time into these models, recognizing it as a significant factor in job acceptance decisions and overall labor market outcomes.

In the literature on job search and commuting time, previous studies have emphasized the importance of commuting time in job satisfaction and wages (van den Berg and Gorter, 1997; Van Ommeren, 2000a; Carra et al., 2016; van Ommeren et al., 2000; Rupert et al., 2009; Flemming, 2020; Le Barbanchon et al., 2021). Our study extends this literature by integrating household search behaviors into the analysis of commuting time, providing a more comprehensive understanding of how households balance these factors.

Additionally, the structural estimation of job search models has been a key focus in the literature, with significant contributions from Flinn and Heckman (1982), Eckstein and van den Berg (2007), Dey and Flinn (2008), Flabbi and Mabli (2018), Flinn et al. (2023), and Salazar-Saez (2023). Our paper advances this field by developing a joint model of household search and commuting time, offering new insights into the interplay between these elements in labor market decisions. The results of our analysis reveal significant gender differences in job search behavior and the valuation of commuting time.

The remainder of this paper is organized as follows. Section 2 describes the model and the equilibrium conditions. Section 3 presents the data, the estimation method, and the identification discussion. Section 4 discusses how we measure the marginal willingness to pay for commuting time and presents the estimation results. Finally, Section 5 presents our final remarks and discusses future plans to extend our analysis.

2 The Model

We extend a partial equilibrium job search model, in the spirit of Lippman and McCall (1976), by adding commuting time as job amenity, as in van den Berg and Gorter (1997) or more recently Van Ommeren (2000a), in a household decision environment similar to Dey and Flinn (2008) and Flabbi and Mabli (2018). In the model the job offers distribution, that characterizes both wages and distance to the job (hence commuting time), is exogenous and household members make decisions on their labor market status taking into account the labor market status of their partner. In this environment, each household value the consumption derived from their labor income as well as the time dedicated to non labor market activities; which in tun is affected by decision taken with respect to the time dedicated to work and dedicated to commute. Our model adds the household dimension to the job search with commuting time literature and adds the commuting time dimension (as job amenity) to the household search literature.

2.1 Environment

Time is continuous and the economy is populated by infinitely lived individuals who discount the future at rate ρ. There are two types of workers, men indexed by 1 and women indexed by 0, that are match together in a household. We do not model how household are formed, instead we assume they already exist and the match last forever. At any point in time, each member of the household can be in one of the two possible labor market states: unemployed and employed. The household derives utility from consumption and from leisure (or more generally, non labor market activities). More specifically, the instantaneous utility function is $u(c_1 + c_0, l_1, l_0)$, where $c = c_1 + c_0$ is the household consumption and l_1 and l_0 are leisure of men and women, respectively.

A job offer arrive at gender specific Poisson rate λ_i, with $i = 1, 0$. We consider only full time jobs.[1] A job offer is a vector (w, t), where w and t are weekly wage and weekly commuting time (in hours), respectively. These offers are draws from the gender specific joint distributions

[1]As shown in Figure 1b, in the Chilean labor marker, the empirical application we are considering, married women tend to adjust more on commuting hours than on flexibility related with hours worked.

$G_i(w,t)$, with $i = 1, 0$. When working, individuals spend h (exogenously given) hours a week working full time. Finally, jobs are terminated exogenously at gender specific Poisson rates δ_i, with $i = 1, 0$.

When unemployed, each member of the household spend s_i hours searching for a job and the household receives y as non labor market income (such as unemployment benefits, government subsidies, transfers, etc). Putting all these ingredients together, the household solves the following lifetime problem choosing the path of each member in the labor market:

$$\max \quad \int_0^\infty u(c_1 + c_0, l_1, l_0) e^{-\rho t} dt \tag{1}$$

subject to

$$\begin{aligned} c_1 + c_0 &= w_1 \mathbb{I}_1^e + w_0 \mathbb{I}_0^e + y \\ l_1 &= 1 - (h_1 + t_1)\, \mathbb{I}_1^e - s_1 \mathbb{I}_1^u \\ l_0 &= 1 - (h_0 + t_0)\, \mathbb{I}_0^e - s_0 \mathbb{I}_0^u \end{aligned}$$

where $\mathbb{I}_i^j$ are indicator variables that take the value of 1 if the state j for individual type i is employed (e) or unemployed (u). Finally, we assume that there is no bargaining involved in the decision-making process of the household; therefore household members engage in a leader-follower game when making decisions. That is, each member of the household make decision on their labor market status conditional conditional on the current labor market status of his/her partner.

2.2 Value functions

The problem in equation (1) can be characterized more compactly in its recursive form by using the Bellman equations for each labor market state. To do so, let's first define the value functions for a household in each possible state of its members. Let $V(w_1, t_1, w_0, t_0)$ be the value of a household with both members employed in jobs with wages and commuting times (w_1, t_1) and (w_0, t_0) for the man and woman, respectively. In turn, let $T_i(w_i, t_i)$ be the value of a household in which member i is employed in a job with wage and commuting time (w_i, t_i), while the other member, $1 - i$, is searching for a job. Finally, let U be the value of a household with both members searching for a job.

The Bellman equation that characterizes the value when both members of the household are employed is defined as follows:

$$\begin{aligned}\rho V(w_1,t_1,w_0,t_0) &= u(w_1+w_0+y,1-h_1-t_1,1-h_0-t_0)\\ &+\delta_0\left[T_1(w_1,t_1)-V(w_1,t_1,w_0,t_0)\right]\\ &+\delta_1\left[T_0(w_0,t_0)-V(w_1,t_1,w_0,t_0)\right] \qquad (2)\end{aligned}$$

When both members of the household are employed, the total weekly income of the household, and therefore their consumption, is given by $w_1 + w_0 + y$. Moreover, each member of the household spends a total of $h_i + t_i$ hours per week working and commuting, which leaves a total of $1-h_i-t_i$ hours per week to devote to non-labor market activities. Furthermore, while working, a termination shock can occur with Poisson rate δ_i to the i member of the household, generating a loss of value of $T_i(w_i,t_i) - V(w_1,t_1,w_0,t_0)$, with $i = 1,0$.

The Bellman equation that characterizes the value when both members of the household are unemployed is defined as follows:

$$\begin{aligned}\rho U = u(y,1-s_1,1-s_0) &+ \lambda_1 \int\int \max\left\{U, T_1(w_1,t_1)\right\} g_1(w_1,t_1)dw_1dt_1\\ &+\lambda_0\int\int \max\left\{U,T_0(w_0,t_0)\right\} g_0(w_0,t_0)dw_0dt_0-(\lambda_1+\lambda_0)U \qquad (3)\end{aligned}$$

When both members of the household are unemployed, the total weekly consumption of the household is just its non-labor income y. Moreover, while searching for a job, both members of the household spend hours in that process: specifically, s_1 for men and s_0 for women. Additionally, a job offer (w_i,t_i) arrives at Poisson rate λ_i to the i member of the household, with $i=1,0$. If the offer is acceptable, that is $T_i(w_i,t_i) \geq U$, the offer is accepted, a value gain of $T_i(w_i,t_i)-U$ is realized, and now the i household member becomes employed while the other continues searching for a job. On the contrary, if the offer is not acceptable, both members of the household keep searching for a job.

The Bellman equation that characterizes the value when on member of the household is employed and the other is unemployed is defined as follows:

$$\begin{aligned}\rho T_i(w_i,t_i) &= u(w_i+y, i(1-h_1-t_1)+(1-i)(1-s_1),(1-i)(1-h_0-t_0)+i(1-s_0))\\ &+\delta_i\left[U-T_i(w_i,t_i)\right]\\ &+\lambda_{1-i}\int\int\max\left\{T_i(w_i,t_i),V(w_1,t_1,w_0,t_0),T_{1-i}(w_{1-i},t_{1-i})\right\} g_{1-i}(w_{1-i},t_{1-i})dw_{1-i}dt_{1-i}\\ &-\lambda_{1-i}T_i(w_i,t_i); \qquad i=1,0 \qquad (4)\end{aligned}$$

When only the i member of the household is working, the total weekly consumption of the household is given by $w_i + y$, while he/she spends $h_i + t_i$ hours per week in the labor market (working and commuting). On the contrary, the member $1-i$, who is searching for a job, spends s_{1-i} hours per week making an effort to find a job. Two events can occur: a termination shock for the employed member of the household or a job offer arrival for the unemployed member of the household. In the former case, the termination shock occurs with Poisson rate δ_i to the i member of the household, generating a loss of value of $U - T_i(w_i, t_i)$. In the latter case, with Poisson rate λ_{1-i}, a job offer arrives for the $1-i$ member of the household, triggering the following decisions: (1) if the offer is acceptable while maintaining the status quo of the i member of the household, which is the case if $V(w_1, t_1, w_0, t_0) \geq T_i(w_i, t_i)$ and $V(w_1, t_1, w_0, t_0) \geq T_{1-i}(w_{1-i}, t_{1-i})$, then the $1-i$ member of the household accepts the job (making both members of the household employed), and a value gain of $V(w_1, t_1, w_0, t_0) - T_i(w_i, t_i)$ is realized; (2) if the offer is acceptable for the $1-i$ household member and it is better for the employed member of the household (the i one) to resign and start searching for a new job, which is the case if $T_{1-i}(w_{1-i}, t_{1-i}) \geq T_i(w_i, t_i)$ and $T_{1-i}(w_{1-i}, t_{1-i}) \geq V(w_1, t_1, w_0, t_0)$, then the $1-i$ member of the household accepts the job and a value gain of $T_{1-i}(w_{1-i}, t_{1-i}) - T_i(w_i, t_i)$ is realized; and finally (3) if the offer is not acceptable in any of the previous cases, then both members of the household keep their current labor market state.

2.3 Equilibrium

The optimal decision rules in this model have a reservation value property and depend on the type of transition and the labor market states of the household members. If an individual receives an offer (w, t) while unemployed, they will accept the offer if its present discounted value is higher than the alternative (remaining unemployed when both members of the family are unemployed), i.e., $T(w, t) \geq U$. In principle, there could be a number of acceptable combinations of (w, t); however, given that w and t are closely related by their joint distribution, an individual can evaluate the acceptable wage for a given commuting time $w(t)$ (Rupert et al., 2009). Therefore, the reservation wage is $w_i^*(t_i)$ and satisfies $U = T_i(w_i^*(t_i), t_i)$ with $i = 1, 0$. The decision is then as follows: given an offered commuting time t, the wage offer is acceptable only if $w > w^*(t)$. The $w^*(t)$ function is increasing in t given that $dt/dw = -\frac{\partial T/\partial t}{\partial T/\partial w} > 0$, $\partial T/\partial t < 0$, and $\partial T/\partial w > 0$. This means that an individual is willing to commute more only if the job pays more for that attribute. As will be seen in section 4, this derivative is closely related to our definition of marginal willingness to pay.

Similarly, if an individual receives an offer (w, t) while employed, he/she will accept the offer if its present discounted values is higher that the one in the alternative (searching while the spouse is employed), that is $w(w_1, t_1, w_0, t_0) \geq T_i(w_i, t_i)$ with $i = 1, 0$. Again, in principle there could be a number of acceptable combinations of (w_i, t_i) given the employment status of the spouse (w_{1-i}, t_{1-i}); but given the relationship between w and t there exists a the reservation wage for individual i, $\tilde{w}_i^*(w_{1-i}, t_{1-i}, t_i)$, that satisfies $T_1(w_1, t_1) = V(w_1, t_1, \tilde{w}_0^*(w_1, t_1, t_0), t_0)$ for women and $T_0(w_0, t_0) = V(\tilde{w}_1^*(t_1, w_0, t_0), t_1, w_0, t_0)$ for men. Using the same arguments as before, $\frac{\partial \tilde{w}_i^*(w_{1-i}, t_{1-i}, t_i)}{\partial t_i} > 0$.

Using these ingredients, we define the model equilibrium as follows:

Definition. Given a vector of parameters $\{\lambda_i, \delta_i, \beta_i, \alpha_i\}_{i=1,0} \times \{\gamma, y, \rho\}$ and gender-specific joint probability distributions functions for wages and commuting time $G_i(w, i, t_i)$ with $i = 1, 0$, a steady-state equilibrium in the economy is a set of value functions $\{V(\cdot), T_1(\cdot), T_0(\cdot), U\}$; the reservation values $w_i^*(t_i)$ and $\tilde{w}_i^*(w_{1-i}, t_{1-i}, t_i)$ with $i = 1, 0$; ; and the proportions of households with both members employed, both members unemployed, and one member employed while the other is unemployed. These must satisfy equations 2 to 4 and maintain an invariant distribution of labor market states across individuals and households.

3 Estimation

We structurally estimate the model characterized in equations (2) to (4) using Simulated Method of Moments (SMM) with cross-sectional data for the Chilean labor market, more specifically, the Socio-Economic Characterization Survey (CASEN, for its abbreviation in Spanish) for 2017. Our identification strategy rely on standard arguments of Flinn and Heckman (1982) to identify the parameters of a search model with only supply side cross-sectional data; and of Dey and Flinn (2008) and Flabbi and Mabli (2018) to identify the parameters of a household search model with couples data.

3.1 Data

The data available to estimate the model comes from the Socio-Economic Characterization Survey (CASEN) from 2017, which is a cross-sectional household survey representative at the national level taken every three years. This survey contains information not only on labor market status, monthly labor income, hours worked, and individual characteristics (such as gender, age, marital status and education), but more importantly about the relationships within a household and the weekly time spent commuting from home to the workplace. Questions regarding commuting time were introduced in the 2017 version of the survey.

There are two main reasons for using data from the Chilean labor market. First, although approximately 75% of the population lives in metropolitan and commuting areas, consistent with the OECD average, the per capita built-up area has slightly decreased over the past 30 years. This indicates that the population in metropolitan areas has grown faster than the built-up areas (OECD, 2020), which intensifies the pressure on the infrastructure networks and the provision of basic services. Even-tough Chile has expanded and modernized quite importantly its transportation network (with the implementation of electric buses and the expansion of the metro system), it remains as the country with one of the highest commuting times among the OECD countries: 60 mins per day in Chile vs. 35 mins per day as the average of the OECD countries. Second, Although there has been significant progress, gender gaps remain high in Chile. Indeed, as highlighted by OECD (2021), the earnings gap between men and women is more pronounced in Chile compared to other countries. The median wage for male full-time employees is 12% higher than that of female full-time employees. Additionally, the proportion of low-income workers is disproportionately higher among women, with the share of low-income women being about 1.6 times greater than that of men. Many potential explanations for these remaining gender gaps in labor market outcomes are related to family duties, particularly the presence of children (Cortés and Pan, 2023).

The CASEN survey provides comprehensive information on the labor market characteristics of couples, allowing therefore estimate a household search model like the one describe in the previous section. In particular, it categorizes individuals by type of worker, $\{I_1, I_0\}$, distinguishing between the husband and the wife. For those employed, the survey records weekly wages, $\{w_1, w_0\}$, and weekly commuting time, $\{t_1, t_0\}$, for both spouses. It also details the states in the labor market, represented by $\{I_{1,u=1}, I_{1,e=1}, I_{0,u=1}, I_{0,e=1}\}$, indicating whether each individual is unemployed (u=1) or employed (e=1). Additionally, the survey captures the durations of ongoing employment and unemployment, $\{d_1^u, d_1^e, d_0^u, d_0^e\}$, for both the husband and wife, which helps in understanding the length of time they have spent in their current employment or unemployment state. Complementary to this, the National Time-Use Survey provides data on the time each individual spends searching for a job, $\{s_1, s_0\}$. This combined dataset offers a detailed view of the labor market activities and conditions experienced by couples in Chile.

Our sample consists of households with men and women aged 25 to 55 years who are actively participating in the labor market and living in urban areas. For those employed, we include only full-time employees. We do not include mono-parental households in the analysis. Overall, we have data for 9,273 households.

First, we analyze only participants to simplify the model and compare the results with those in the main literature on labor search and commuting time, which do not model the extensive margin of labor supply. This is admittedly a significant limitation in the analysis, considering that 48% of women of working age do not participate in the labor market. We plan to relax this assumption and explicitly model labor supply decisions in future versions of the paper. Second, we focus on urban areas because the type of model considered here is a good description of the labor market in these areas. Clearly, rural labor markets operate very differently. Third, limiting our sample to individuals aged 25 to 55 years prevents complications related to modeling human capital decisions before entry into the labor market and retirement decisions. Finally, limiting the sample to only full-time employees follows the observation in Figure 1 which suggests that the main margin of adjustment for married women in the Chilean labor market seems to be commuting hours rather than working hours.

Table 1 presents descriptive statistics of the labor market for our sample of households. The first column indicates the statistic presented for men and women. Additionally, as stated in the row labeled "Spouse Labor Market," each statistic is presented based on the labor market status of the spouse: unemployed or employed. As shown in the first group of statistics, 1.1% of households have both members unemployed, while 87.4% have both employed. Households in which the husband is employed and the wife is unemployed represent 7.1%, while households with the opposite situation represent 4.4%.

Regarding weekly wages, men earn more than women on average, regardless of the labor market status of their spouse. However, the wage gap is smaller when both members of the family are employed. Specifically, employed men with unemployed wives earn 225 dollar per week, while women with unemployed husbands earn 179 dollar per week, resulting in a wage gap of approximately 25% in favor of men. Conversely, when both spouses are employed, men earn 266 dollars per week, while women earn 227 dollars per week, reducing the wage gap to around 17% in favor of men. Another interesting observation is that the wage distribution is more spread out for women compared to men, regardless of the labor market status of their spouse. This difference is again more pronounced when the spouse is unemployed, with the standard deviation being 30% higher for women compared to men in this case. When the spouse is employed, the standard deviation is 18% higher for women compared to men.

Men also commute longer hours on average than women, regardless of the labor market status of their spouse. Men commute more than 6 hours per week in any labor market status of their spouse, while women commute 4.9 hours per week if their spouse is unemployed and 5.2 hours per week if their spouse is employed. The gender difference in average commuting time is around 30%. The distributions of commuting times are more spread out for men, with the difference in the standard deviation between men and women ranging from 22% to 25%, depending on the labor market status of the spouse.

Finally, men remain employed for longer periods on average, but they also spend more time in unemployment compared to women. Men stay employed between 7.4 and 8.2 years when their spouse is unemployed and employed, respectively. Women, in turn, remain employed for around 6.5 years regardless of their spouse's employment status. Conversely, in the unemployment state, men remain unemployed for between 12 and 14 months, while women do so for between 10 and 12 months.

3.2 Identification

Our identification strategy follows standard arguments used in previous literature. We can divide the set of parameters into three groups based on the information necessary to estimate the parameters in each group.

The first group consists of the mobility parameters, $(\lambda_i, \delta_i,)$ with $i = 1, 0$, which, as shown in Flinn and Heckman (1982), are mainly identified by the steady-state proportion of individuals (and in our case, households with members in different labor market states) in each labor market state and by the duration information. In this type of search model, which does not feature duration dependence, the hazard rate out of each labor market state is constant and therefore follows an exponential distribution. The hazard rate is closely related to the average duration in those states (it is actually its inverse). Additionally, the steady-state proportions impose the restriction that, in any labor market state, the outflows must be exactly compensated by the corresponding inflows.

The second group consist in the gender-specific joint probability distributions functions for wages and commuting time $G_i(w_i, t_i)$ with $i = 1, 0$. We make a parametric assumption defining the joint distributions of wages and commuting time as a bivariate log-normal distribution. That is:

$$\begin{bmatrix} \log w \\ \log t \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu_w \\ \mu_t \end{bmatrix}, \begin{bmatrix} \sigma_w^2 & \sigma_{wt} \\ \sigma_{wt} & \sigma_t^2 \end{bmatrix} \right)$$

which is characterized by the gender-specific parameters $\{\mu_{i,w}, \sigma_{i,w}, \mu_{i,t}, \sigma_{i,t}, \rho_{i,w,t}\}_{i=1,0}$. Log-normal distributions are widely used in the literature because they provide clear identification of parameters based on observed data and have shown empirical success in fitting earnings and wage distributions very well (Eckstein and van den Berg, 2007). As Flinn and Heckman (1982) discusses in detail, the observed data—in our case, wages and commuting time—are the accepted attributes of a job. Therefore, the observed distribution is a truncation of the primitive one at the minimum accepted values of these attributes (the reservation values). Flinn and Heckman (1982) show that if the distribution belongs to the location and scale class of distributions, the primitive distribution can be recovered from the truncated one when the truncation point is known (that is, this class of distribution satisfies the recoverability condition). The log-normal distribution belongs to this class of distributions.

In our case, we have a bivariate log-normal distribution, and in principle, the observed data is characterized by a truncated version of the primitive one in both dimensions: wages and commuting time. However, given the reservation values discussed in Section 2, the observed data can be characterized, for any value of the commuting time t, by the truncated version of the conditional distribution in the dimension of wages w, at $w^*(t)$. The key point for our identification strategy is that the conditional distribution of $\log w$ given $\log t$ is also normally distributed $\log w \mid \log t \sim \mathcal{N}\left(\mu_{w|t}, \sigma^2_{w|t}\right)$ where $\mu_{w|t} = \mu_w + \rho_{w,t}\frac{\sigma_w}{\sigma_t}\left(t - \mu_t\right)$ and $\sigma^2_{w|t} = \sigma^2_w\left(1 - \rho^2_{w,t}\right)$. This means the conditional distribution also belongs to the location and scale class of distributions and satisfies the recoverability condition. This, in turn, implies that the parameters of the primitive offer distribution are identified from the pair of accepted wages and commuting time information.

The final group of parameters is related to the utility function. As our identification strategy in this case closely follows Flabbi and Mabli (2018), we assume a constant relative risk aversion (CRRA) parametric form for the instantaneous utility function, which is:

$$u\left(c, l_1, l_0; \gamma, \beta, \alpha\right) = \left(1 - \alpha_1 - \alpha_0\right)\frac{c^\gamma - 1}{\gamma} + \alpha_1\frac{l_i^{\beta_1} - 1}{\beta_1} + \alpha_0\frac{l_j^{\beta_0} - 1}{\beta_0}$$

is characterized by the gender-specific parameters $\{\beta_i, \alpha_i\}_{i=1,0}$ and a household parameter γ. The parameter γ measure the degree of risk aversion with respect to consumption, the parameters α_i measures the degree of risk aversion with respect to the time dedicated to non-market activities by the household member i, and β_i measures the relative importance of the time dedicated to non-market activities by the household member i in the household utility function.

As the literature have shown, a household search model equilibrium based on a linear utility function is different from an individual search model equilibrium for each spouse when it is based on concave utility function (Guler et al., 2012; Dey and Flinn, 2008; Flabbi and Mabli, 2018). This is crucial for identification. Risk aversion creates a correlation between the labor market decisions of both household members. One spouse's reservation wage depends on the other spouse's labor market status (wages and commuting time) only if the utility function is nonlinear (Flabbi and Mabli, 2018). Therefore, if the transition probabilities and the accepted wages observed in the data are influenced by the spouse's labor market states, we can identify the γ, β_1, and β_0 parameters. This means that differences in wages and commuting times accepted by husbands and wives in different labor market states provide information on preferences. Moreover, differences in observed choices of commuting time particularly, and consequently non-market activities, by each household member provide information on the α_1, and α_0 parameters.

Putting all pieces together, we have a total of 20 parameters to identify:

$$\Theta = \{\lambda_i, \delta_i, \mu_{i,w}, \sigma_{i,w}, \mu_{i,t}, \sigma_{i,t}, \rho_{i,w,t}, \beta_i, \alpha_i\}_{i=1,0} \times \{\gamma, y\}$$

3.3 Estimation Method

We estimate the parameters of the model using the Method of Simulated Moments (MSM). Let Θ represent the set of parameters to be estimated, M_N^D denote the set of appropriately chosen statistics derived from our data sample of size N, and $M_T(\Theta)$ indicate the corresponding set of simulated statistics extracted from a sample of size T obtained from the steady-state equilibrium implied by Θ. Our MSM estimator $\hat{\Theta}$ is defined to satisfy:

$$\hat{\Theta}_{N,T}(W) = \text{argmin}_{\Theta} \frac{1}{2} \left[M_N^D - M_T(\Theta)\right]' W_N \left[M_N^D - M_T(\Theta)\right] \tag{5}$$

where W is a symmetric, positive-definite weighting matrix. We use the inverse of the bootstrapped variance of each moment in the sample to construct the weighting matrix. The set of chosen moment statistics in equation (5) can be divided into five groups.

First, we consider the proportions of households where both members are employed, households where the man is employed and the woman is unemployed, households where the man is unemployed and the woman is employed, and households where both members are unemployed. Additionally, we include the proportion of employed men (relative to all men) and the proportion of employed women (relative to all women). This results in a total of six moment statistics.

The second group relates to the durations of employment and unemployment states. We include the average and standard deviation of employment duration for men and women when both members of the household are employed, as well as when one member is employed and the other is unemployed. Additionally, we include the average and standard deviation of unemployment duration when both members of the household are unemployed, and when one member is unemployed while the other is employed. This results in a total of sixteen moment statistics.

The third group includes the average and standard deviation of weekly wages in US dollars for employed men and women, conditional on the employment status of the spouse. This includes cases when both members of the household are employed, as well as when one member is employed while the other is unemployed. This results in a total of eight moment statistics.

Similarly, the fourth group includes the average and standard deviation of weekly commuting time, from home to work and back, in hours for employed men and women, conditional on the employment status of the spouse. This results also in a total of eight moment statistics.

The final group of moment statistics relates to the correlation between weekly wages and weekly commuting time, separately for men and women, both when both members of the household are employed and when one member is employed while the other is unemployed. This results in a total of four moment statistics.

Overall, we have 42 moment statistics to estimate a total of 20 parameters. We use the Nelder-Mead simplex algorithm to minimize equation (5) and employ bootstrapping to compute standard errors.

3.4 Results

The estimated parameters are presented in Table 2. The arrival rate of job offers (λ) implies that job offers arrive on average every 2.6 months for husbands and every 3.1 months for wives. In turn, the termination rate parameters (δ) indicate that husbands and wives stay in a given job for an average of 53 and 42 months, respectively.

The parameters of the bivariate log-normal distribution ($\mu_w, \sigma_w, \mu_t, \sigma_t, \rho_{w,t}$) imply that the average wage offer for men is 243 dollars per week, while it is 205 dollars per week for women. This represents a 19% gender gap in wage offers. Additionally, the standard deviation of wage offers is 191 dollars per week for men and 153 dollars per week for women, indicating that the distribution of wage offers is 25% more spread out for men.

Furthermore, the average commuting time implicit in job offers is 4.7 hours per week (0.058 times the normalization of 80 hours) for men, with a standard deviation of 3.9 hours per week. For women, the average commuting time implicit in job offers is 3.8 hours per week (0.048 times the normalization of 80 hours), with a standard deviation of 3.2 hours per week. Therefore, job offers received by women have an average commuting time that is 24% lower compared to those received by men.

The parameters of the utility functions indicate that the importance of time dedicated to non-labor market activities (represented by the β parameter) is higher for women, at 0.9, compared to 0.64 for men. This result is consistent with the fact that, in Chile, home duties are typically performed by women. Regarding the curvature of the utility function with respect to the time dedicated to non-labor market activities (parameter α), the results—0.05 for men versus 0.21 for women—indicate that the marginal utility of each hour of non-labor market activities is consistently higher for women. Moreover, the differences become more pronounced with each less hour dedicated to non-labor market activities. This is consistent with the higher marginal value women place on hours dedicated to home duties.

Finally, the parameters estimated at the household level, common to both men and women, indicate that non-market income (y) tends to be very low and that the utility function is highly concave with respect to household expenditure on consumption (γ).

4 Marginal Willingness to Pay Measures

4.1 Definitions

Following van Ommeren et al. (2000), we define the Marginal Willingness to Pay (MWP) as the additional amount of money a worker is willing to pay for a job attribute—in our case, the time of commute. Negative values of the MWP are therefore interpreted as the amount of money a worker is willing to sacrifice in order to have a better position in other attributes. Formally:

$$MWP = \frac{\partial \text{E[Lifetime Utility]}}{\partial t} \Big/ \frac{\partial \text{E[Lifetime Utility]}}{\partial w} \tag{6}$$

As stated in equation 6, the MWP compares the relative importance of the current attributes of wages (w) and commuting time (t) for expected lifetime utility. This comparison considers not only the current position in the labor market but also potential future labor market opportunities. What is relevant for our paper is that the expected lifetime utility, and therefore the MWP, depends not only on the individual's position in the labor market but also on the labor market position of other household members. Using the notation from section 2, we can formally write the analogous of equation 6 as:

$$MWP_j^{spouse\ u}(w_j, t_j) = \frac{\partial T_j(w_j,t_j)}{\partial t_j} \Big/ \frac{\partial T_j(w_j,t_j)}{\partial w_j} \tag{7}$$

$$MWP_j^{spouse\ e}(w_j, t_j, w_{-j}, t_{-j}) = \frac{\partial V(w_j,t_j,w_{-j},t_{-j})}{\partial t_j} \Big/ \frac{\partial V_j(w_j,t_j,w_{-j},t_{-j})}{\partial w_j} \tag{8}$$

for $j = 1, 0$.

4.2 Results

Figures 2 and 3 presents the estimation of the MWP for women and men respectively using the definitions in equations 7 and 8, and the value functions that solve equations 2 to 4 given the point estimated presented in Table 2.

We define three levels of individual wages to understand the differences in MWP for commuting time relative to an individual's labor market position. A low wage is defined as approximately half the average wage, around 100 dollars per week. A mid wage is close to the average, around 250 dollars per week. Lastly, a high wage is roughly three times the average wage, around 750 dollars per week.

In panel (a) of Figures 2 and 3, we present the Marginal Willingness to Pay (MWP) for women and men when their spouse is unemployed, across the three defined wage levels. The MWP for men is observed to be twice as high as that for women and increases with their own wage. As commuting time increases, the gap in MWP between men and women decreases, eventually closing for very high commuting times. Notably, the slope of the MWP with respect to wages is particularly steep for men.

In panel (b) of Figures 2 and 3, we present the ratio of the Marginal Willingness to Pay (MWP) for women and men, respectively, when their spouse is employed compared to when their spouse is unemployed, as a function of the spouse's wage. We again differentiate between the three defined wage levels. The MWP is highly dependent on the labor market status of the spouse, for both men and women. Comparing the MWP of an individual with an employed spouse to that of an individual with an unemployed spouse, we find that the gap in MWP increases with the spouse's wage (given an average commuting time of 6 hours a week). This relationship is particularly steep for low-income levels of the employed member of the family.

5 Counterfactual Experiments

In the model, we identify three potential sources of differences in employment outcomes between husbands and wives. First, there is a difference in the utility derived from leisure (non-labor market activities), which can be interpreted as a gender difference in the valuation of home production and caregiving responsibilities. Second, the job offer distributions vary, which can be understood as gender differences in the availability of information, types of jobs being searched for, discrimination, etc. Third, there are differences in labor market dynamics, which can be interpreted as gender differences in the intensity of job search, job instability, and discrimination.

To identify the main drivers of gender differences in labor market outcomes with respect to wages and commuting time, we perform two counterfactual simulations. In the first simulation, we equalize the job offer distributions to those estimated for men, imposing $G_0(w_0, t_0) = G_1(w_1, t_1)$ at the parameters estimated for men. In the second simulation, we additionally equalize the labor market dynamics to those estimated for men. On top of imposing $G_0(w_0, t_0) = G_1(w_1, t_1)$, we also impose $\lambda_1 = \lambda_0$ and $\delta_1 = \delta_0$ at the parameters estimated for men. The Table Table 3 show the results of these counterfactual experiments.

The first column presents the benchmark results, which are the simulated outcomes for wages and commuting time based on the point estimates from Table 2. As expected, both men and women earn more when their partner is employed. Regarding commuting time, the differences between men and women, conditional on employment status, are not very pronounced. For example, men with unemployed partners travel only 0.2 hours more per week than those with employed partners. The average gender wage gap in the benchmark is 30%, while the gap in commuting time ranges between 23% and 28% (see bottom panel). When we equalize the job offer distribution—effectively eliminating potential differences in the availability of information, types of jobs being searched for, and discrimination between men and women—we completely close the wage gap. In fact, some of the gaps in commuting time even reverse (see column 2). This indicates that the job offer distribution is the primary driver of gender differences in both wages and commuting time. Finally, when we further equalize the dynamics of the labor market, the gaps remain similar to those observed when only the job offer distributions are equalized (see column 3). In this case, differences in preferences related to the value of non-labor activities become the main source of gender disparities. Notably, these preferences do not result in significant disadvantages for women; in some cases, they even favor them.

6 Concluding Remarks

In this paper we develop a household search model for workers where a job is characterized by two attributes, wage and commuting time, to study how household members' employment status influences their own and other members' marginal willingness to pay for reduced commuting time.

We structurally estimate the model using data from Chile. There are two main reasons for using data from the Chilean labor market in this study. First, despite significant transportation improvements, Chile has one of the highest commuting times among OECD countries. Second, gender gaps remain high in Chile, with a high proportion of low-income workers among women. The median wage for male full-time employees is 12% higher than for female employees, and the share of low-income women is about 1.6 times greater than that of men, often due to family duties and the presence of children.

We uncover several key insights. Our analysis reveals that men exhibit a higher Marginal Willingness to Pay (MWP) for reduced commuting time compared to women. Specifically, men's MWP is twice as high as women's. Additionally, the MWP for both men and women increases with their own wages and their spouse's wages. This suggests that higher household income allows individuals to prioritize shorter commutes, potentially improving overall job satisfaction and work-life balance. We find significant gender differences in job search behavior and the valuation of commuting time. Women are generally more sensitive to commuting time than men, reflecting the greater weight they place on non-market activities and caregiving responsibilities.

Additionally, differences in offer distributions explain the gaps in commuting time. This also partially explains wage gaps.

The motivation behind this study stems from the persistent gender wage gap and the under-explored role of commuting time in shaping labor market outcomes. Previous research highlights the importance of flexible working conditions for women, yet the trade-offs between wages and commuting time have received limited attention. By focusing on dual-earner households, we aim to capture the complexities of joint decision-making processes and their implications for labor-market behavior.

While our study provides valuable insights, several avenues for future research could enhance our understanding of labor-search dynamics. First, our current model focuses on individuals who actively participate in the labor market. We plan to extend the model to include non-participation decisions, particularly for women who may opt out of the labor force because of caregiving responsibilities. Second, it might be valuable to analyze how the interplay between commuting time, wages, and job search behavior varies across educational levels in the future. This involves examining potential sorting mechanisms, such as skill-based sorting in job matches. Third, the presence of children and other dependents can significantly influence job-search behavior and the valuation of commuting time. We plan to explore how family composition affects labor market outcomes and the MWP for commuting time in the future. Finally, integrating moving decisions into the model could provide insights into how households balance job opportunities with residential location choices. This is particularly relevant for understanding how infrastructure improvements and changes in housing markets impact labor market behavior.

In conclusion, this paper contributes to the literature on labor economics by highlighting the importance of commuting time in couples' job search and acceptance decisions. Our findings suggest the need for tailored policy interventions that consider gender-specific labor market behavior and the unique challenges faced by dual-earner households.

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Table 1: Descriptive Statistics

	Men		Women	
Spouse Labor Market	U	E	U	E
Labor market state				
U	0.011	0.044	0.011	0.071
E	0.071	0.874	0.044	0.874
Weekly Wages (US$)				
Mean	225.36	266.17	179.34	226.90
SD	181.29	225.56	136.00	191.66
Weekly Commuting Time (Hours)				
Mean	6.82	6.15	5.20	4.87
SD	5.44	5.09	4.25	4.14
Duration (Months)				
Mean (E)	88.57	98.58	79.62	81.21
Mean (U)	14.42	11.91	12.34	9.80

NOTE: $N = 9273$ households. The cross-sectional moments are computed from CASEN 2017. SD = Standard deviation; E = employed full time; U = unemployed.

Table 2: Estimated Parameters

	Men		Women	
	Parameter	Std.Error	Parameter	Std.Error
λ	0.3876	(0.01497)	0.3244	(0.03646)
δ	0.0188	(0.01755)	0.0238	(0.0883)
μ_w	0.6432	(0.06641)	0.4994	(0.06244)
σ_w	0.6973	(0.02201)	0.6634	(0.0065)
μ_t	-3.0972	(0.20160)	-3.3008	(0.4658)
σ_t	0.7166	(0.03273)	0.7286	(0.00996)
$\rho_{w,t}$	-0.0083	(0.04654)	0.0013	(0.08838)
β	0.6429	(0.01647)	0.8950	(0.03674)
α	0.0484	(0.05055)	0.2106	(0.07423)
	Household			
γ	0.1528	(0.9512)		
y	0.0073	(0.6725)		
Loss	973.78			

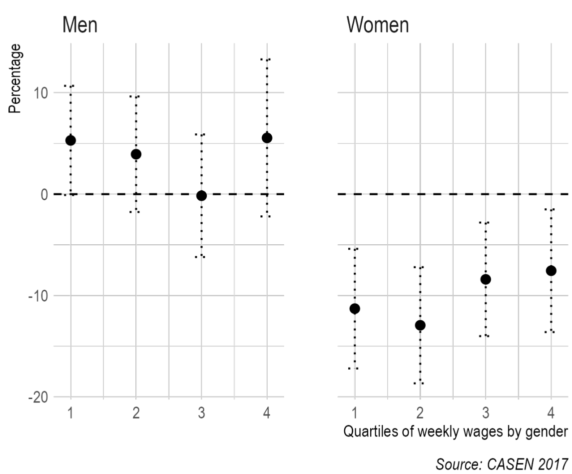
NOTE: Bootstrapped standard errors in parenthesis. Fixed parameters $\rho = 0.1$, $h_1 = h_0 = 44/80$, $s_1 = 14/80$, and $s_0 = 10/80$.

Table 3: Counterfactual Experiments

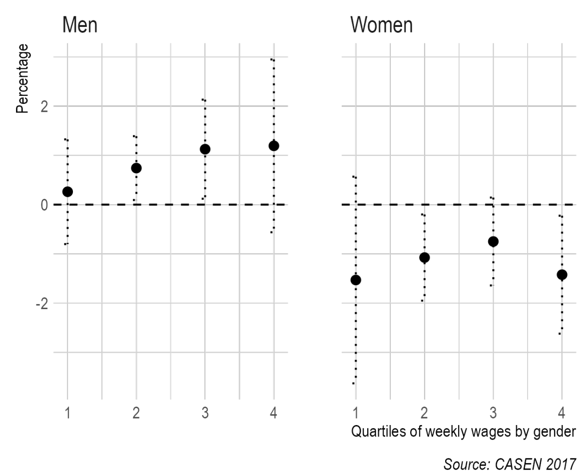
	Benchmark	Same Offer Distributions	Same Offer Distributions and L.M. Dynamics
Average Wages (US$ per Week)			
Men with couple employed	292	298	302
Men with couple unemployed	284	292	293
Women with couple employed	222	281	282
Women with couple unemployed	218	295	309
Average Commuting Hours per Week			
Men with couple employed	4.6	4.5	4.4
Men with couple unemployed	4.8	4.6	4.3
Women with couple employed	3.7	4.7	4.6
Women with couple unemployed	3.7	4.8	4.6
Ratio (Men/Women)			
Wages - Couple employed	1.32	1.06	1.07
Wages - Couple unemployed	1.31	0.99	0.95
Commuting - Couple employed	1.23	0.95	0.96
Commuting - Couple unemployed	1.28	0.95	0.94

NOTE: Benchmark presents the labor market outcomes simulated at the point estimates of table 2.

Figure 1: Average difference in commuting and working hours between married and single individuals by income quartiles (Chile, 2017)

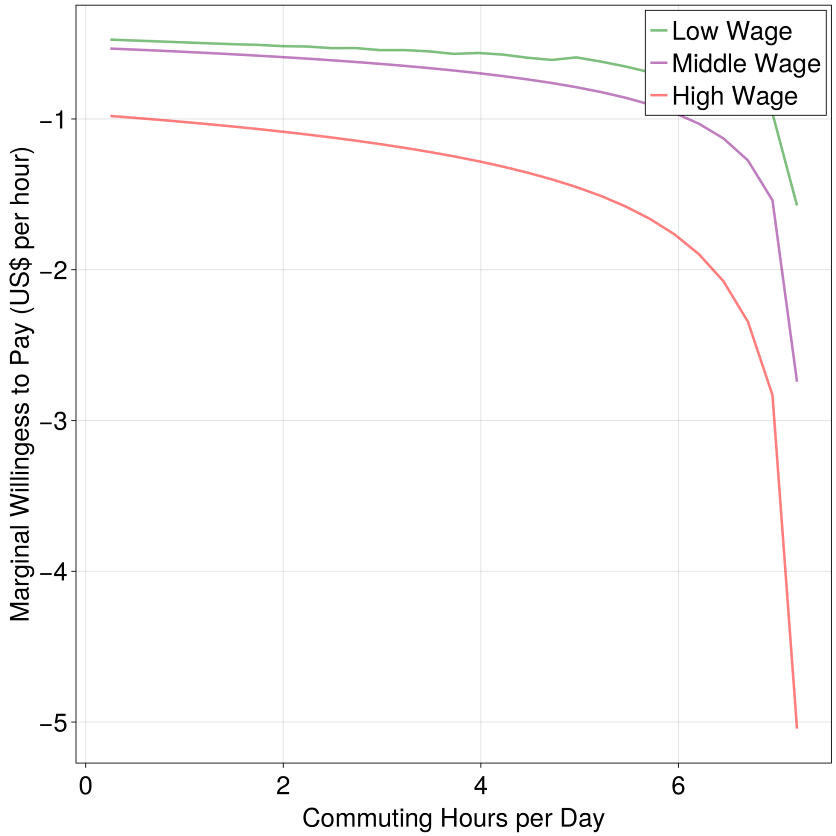


(a) Weekly hours devoted to commuting

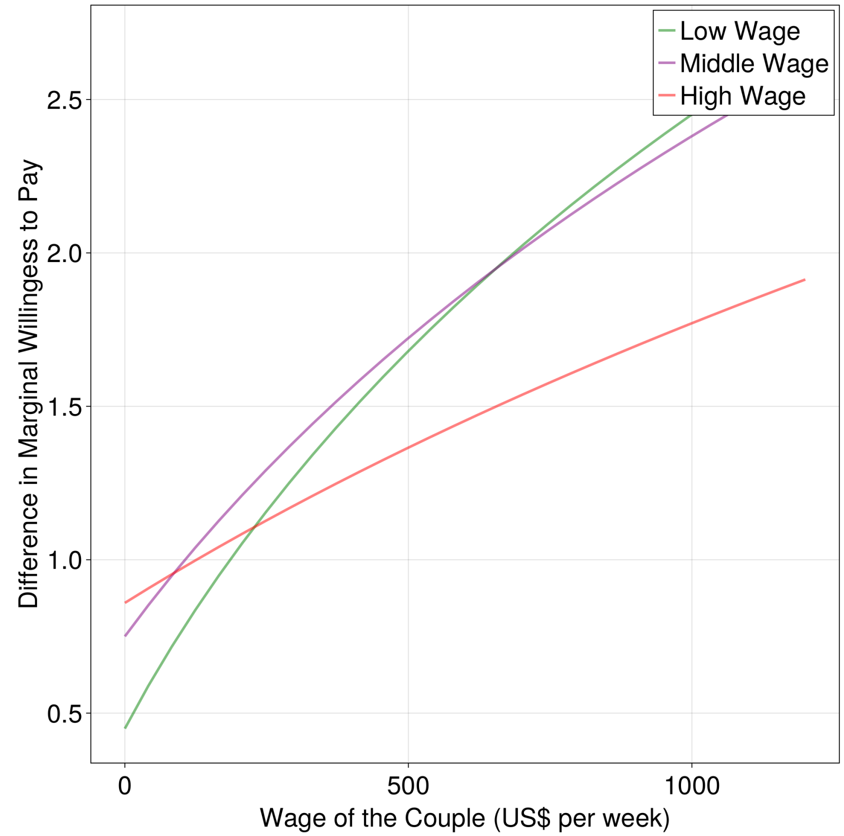


(b) weekly hours worked

Figure 2: Women's Marginal Willingness to Pay

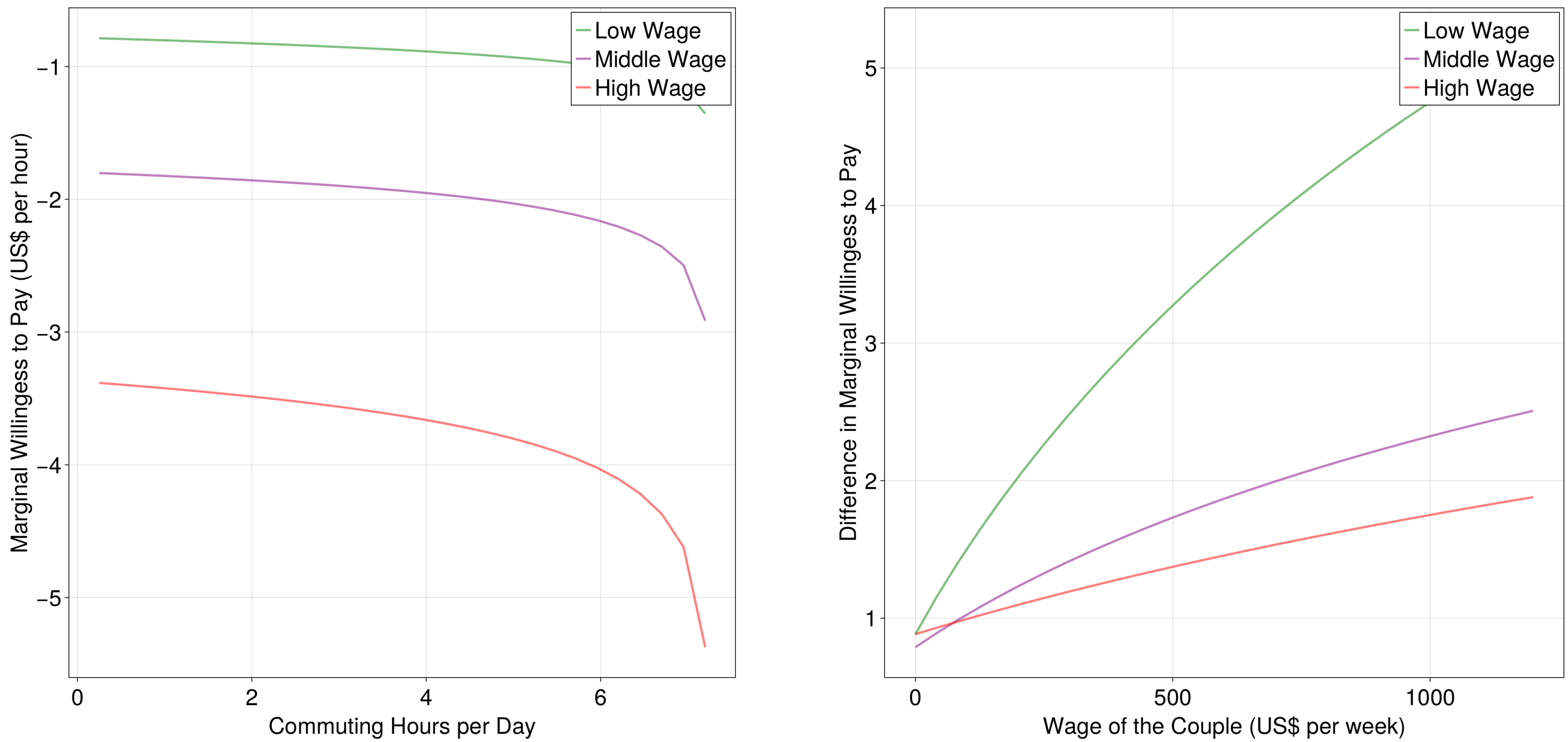


(a) $MWP^{\text{Husband Unemployed}}$



(b) $MWP^{\text{Husband Employed}}/MWP^{\text{Husband Unemployed}}$ as function of husband's wage

Figure 3: Men's Marginal Willingness to Pay



(a) $MWP^{\text{Wife Unemployed}}$

(b) $MWP^{\text{Wife Employed}}/MWP^{\text{Wife Unemployed}}$ as function of wife's wage