Gender Wage Gap and Firm Market Power: Evidence from Chile

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Abstract

The main aim of this work is to explain the Chilean gender wage gap using a dynamic monopsony model to estimate the labor supply elasticities at the firm level. Our results suggest that the elasticities of labor supply to firms are small, which implies that firms have labor market power. We also found that depending on the especification, Chilean men would earn approximately 19% - 28% more than women as a result of the difference in labor supply elasticities by gender, ceteris paribus. Furthermore, we find that in the long run, the magnitude of between-firm differences in elasticities are higher than within-firm differences, which suggests that the gender wage gap is driven by structural factors that generate gender sorting to firms. Finally, using the same methodology, we find that the elasticities for a high-income countries (e.g. the United States) are higher than those obtained for a middle-income country (e.g. Chile) for both men and women, which siggests higher labor market frictions in middle-income countries. The main difference between USA and Chile comes from the low labor supply elasticity of Chilean women, which appears to be explained from their low recruitment elasticity from nonemploeyment.

Keywords: Gender Pay Gap, Dynamic Monopsony, Elasticity of Labor Supply, Worker Mobility, Chile
JEL Classification: J16, J18, J42, J62, J71

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1 Introduction

The gender pay gap has been studied for decades in economics (e.g. Altonji and Blank 1999, Bertrand 2011 and Blau and Kahn 2017 for surveys), mainly but not exclusively because the diminished economic power of women has detrimental effects on society, which affects pensions, health, poverty, fiscal policy, etc. (e.g., European Commission 2013). Although there is a vast body of literature that studies the gender wage gap, most studies considered perfectly competitive labor markets assuming a perfectly elastic labor supply (Becker, 1971). This competitive approach assumes that two workers with identical characteristics doing identical jobs at the same firm must be paid identical wages. If they are not, the residual difference must be due to discrimination. Becker pointed out that competitive forces should reduce or eliminate discrimination in the long run because the least discriminatory firms would have lower costs of production and should drive more discriminatory firms out of the market.

Studies related to monopsony models in the labor market have questioned Becker's approach because of the existence of frictions in the labor market (Robinson, 1933; Madden, 1973; and Black, 1995). The new monopsony literature (Manning 2003) emphasizes that monopsony power may arise even if there are many firms competing for workers. These models yield upward-sloping firm-level labor supply curves (even without concentration on the demand side) due to search frictions, heterogeneous preferences among workers and mobility costs. Therefore, as noted by Webber (2016), in the new monopsony literature, the word "monopsony" is a synonymous with monopsonistic competition, imperfect competition, finite labor supply elasticity, an upward-sloping labor supply curve to the firm and basically any departure from perfect competition.

This literature suggests that the monopsonistic framework can explain how discriminatory gender wage differences arise and persist if firms wield greater monopsony power over female workers than male workers. For this to hold, the supply of labor of women to the firm must be less wage-elastic than that of men. The lower labor supply elasticity of women may be due to various factors, such as: a) Family locational decisions (Cooke et al. 2009, Benson 2014 and Webber 2016), b) Workers' preferences (Bonin et al. 2007, Albanesi and Olivetti 2009), c) Lower bargaining power (Croson and Gneezy 2009, Card et al. 2016, Cruz and Rau 2017), d) Psychological attributes (Mueller and Plug 2006 , Borghans et al. 2014) and e) Sorting (Card et al. 2016, Cruz and Rau 2017).

Because of these factors, women may have fewer outside options than men, which makes their labor supply to the firm more inelastic. Due to data constraints, only recently have studies started considering the effect of imperfect competition in the labor market on the gender wage gap. Most of these studies have focused at the market level and found that male elasticity is higher than female elasticity, and this difference can explain approximately one-third of the gender wage gap. Until now, there is very little evidence at the firm level, and it is mostly for the United States. Furthermore, it can be argued that market imperfections (i.e., search frictions, mobility costs, etc.) are more prevalent in middle- and low-income countries than in the United States due to higher poverty rates, greater difficulty in starting businesses, poorer information technologies and transportation infrastructure, fewer education opportunities, and lower unionization rates (e.g., Jackson and Jabbie 2019). Additionally, empirical studies have noted that larger, more informal sectors and more widespread discrimination in many middle- and low-income countries are particularly harmful to female equality and mobility (Chioda 2011; World Bank 2012).

Hence, our work aims at calculating and comparing labor supply elasticities at the firm level by gender for Chile with those obtained for the U.S., which indirectly examines the prevalence of labor market frictions in both cases. We focused on Chile because it is an interesting case to study as it is a developing economy that shares similarities with developed countries in terms of labor market institutions (e.g., unemployment insurance, minimum wage and active labor market programs) but has not completed the transition to economic development (e.g., a significant share of its labor market is informal work, high wage inequality, low quality of education, etc.).

We used the Chilean Unemployment Administrative Database. This panel database considers information about individuals who were employed in the private sector (as dependent workers) since October 2002 and decided to affiliate with this system and individuals who were not working at that time but found a dependent job in the private sector after that date.[1] The mentioned data set includes all required variables, which enables us to study the dynamics of the labor market by firm because we can identify the employee and employer in each time period, wages and separations, etc.

This paper is structured as follows. Section 2 presents a literature review of previous works that used dynamic monopsony models. Section 3 introduces a simple theoretical model that highlights the importance of the labor supply elasticity in the gender wage gap. Section 4 presents our empirical strategy. Section 5 describes the data and provides summary statistics of the key variables to estimate our models. Section 6 presents the main results of our work, and Section 7 includes concluding remarks and a discussion of avenues for future research.

[1] We cover the period of 2010-2019 in this study. By January 2010, the number of affiliated individuals reached 6.3 million (i.e., 86% of the labor force in Chile, as suggested by the Superintendecia de Pensiones and Instituto Nacional de Estadísticas).

2 Literature Review

Previous literature on the gender wage gap is huge (see Blau and Kahn 2017 for a recent survey), but it generally assumes competitive labor markets. Only recently have studies started considering the effect of imperfect competition in the labor market on the gender wage gap. Manning (2003) estimated the labor supply elasticities for American and British data sets: the Panel Study of Income Dynamics and National Longitudinal Study of Youth from the United States and the Labour Force Survey and British Household Panel Study from the United Kingdom. Labor supply elasticities are notably low for all four data sets (0.68 - 1.4), but he does not find differences by gender. Because Manning used data sets based on supply-side individual- or household-level surveys, he could not adecuately control adequately for firm-specific determinants of transition behavior.

Due to data constraints, only recently have studies considered the effect of imperfect competition in the labor market on the gender wage gap. Among the first, Barth and Dale-Olsen (2009) studied the gender wage gap using this framework for Norway. They found that labor supply elasticities were approximately 1.1 - 1.4 for men with low and high education levels and 1.0 -1.1 for women with low and high education levels respectively. Next, a special issue of the *Journal of Labor Economics* (2010) presented a few studies that analyzed the gender wage gap with monopsonistic labor markets. In this issue, Ransom and Oaxaca (2010) and Hirsh et al. (2010) estimate the male and female labor supply elasticities; the former used data from one regional grocery retailer in the United States, and the latter used German panel data.

Ransom and Oaxaca (2010) used one of the implications of monopsony models, which is the fact that under certain conditions, the labor supply curve might be calculated by the wage separation elasticity. Ransom and Oaxaca exploited the differences in wages and separations between job titles in a firm. Furthermore, they did not control for firm-specific controls (as in Manning 2003) and implicitly treated wages of workers as exogenous; they claimed that employers had no control over wages because wages for each job title were fixed by bargaining. The authors found differences in labor supply elasticity between males and females, with the latter being smaller than the former (i.e., 2.5 for men and 1.6 for women). Ransom and Oaxaca (2010) relied on a specification in the spirit of Burdett and Mortensen's (1998) equilibrium search model with wage posting, where the transitions to and from nonemployment are wage-inelastic; therefore, the wage-related hire of one firm is the wage-related quit of another firm.

Unlike the study by Ransom and Oaxaca (2010), Hirsch et al. (2010) allowed for wage-elastic transitions to and from nonemployment and controlled the firm characteristics. They used the German-linked employer-employee data set LIAB for the years 2000–2002. Their estimated elasticities were 1.9 to 3.7, depending on specification, with women's elasticity always lower than men's. Their results suggest that new monopsony models imply that firms have substantial monopsony power because the estimated elasticities are small in size. Furthermore, although they did not directly test the difference between men's and women's elasticities, they calculated that it should explain approximately one-third of the observed gender pay gap, which is similar to the result of Ransom and Oaxaca (2010). It is important to note that this result cannot be directly tested in the data used in these studies but is theoretically implied by the difference in gender-specific elasticities at the market level.

Booth and Katic (2011) followed Manning's approach to estimate the elasticity of the labor supply separated by gender using the Household Income and Labor Dynamics in Australia (HILDA) Survey. They found elasticities of 0.76 and 0.61 for men and women, respectively, which are close to the result of Manning (2003) for the UK (0.75). Similarly, Sulis (2011) estimate gender wage differentials in Italy for the period of 1985-1996 using dynamic monopsony models and data from the Italian Administrative Social Security Archive (INPS). The reported elasticities for men and women are smaller than those found in previous literature, being 0.4 and 0.3 respectively.

Until now, all empirical studies have calculated the elasticity at the market level. Webber (2015) extended the theoretical and empirical model to the firm level using thousands of firms in several industries for the United States instead of one firm, as used by Ransom and Oaxaca (2010). He found support in the data for dynamic monopsony models. Webber (2016) extended his previous work by breaking down the elasticity by gender. He estimated the male and female labor supply elasticity by firm for the United States and used this information to study the gender pay gap. In both studies, Webber found substantial search frictions in the United States labor market, where females faced a higher level of friction than males. He also found that males faced a labor supply elasticity of 0.15 points higher than that for females (i.e., 1.09 versus 0.94), which leads to 3.3 percent lower earnings for women.

We use Webber's approach to the Chilean context to analyze the labor market power of firms and its differences by gender. Furthermore, we also study between versus within firm differences in labor supply elasticities by gender and their magnitudes by industry.

3 Theoretical Model

The starting point of our analysis is a Cobb-Douglas production function, which features constant returns to scale and heterogeneous labor inputs:

$$Q_{jt} = A_{jt} K_{jt}^{\gamma} L_{jt}^{1-\gamma} \tag{1}$$

For simplicity, we assume the capital stock of the firm (i.e. non-labor inputs summarized by K) is fixed, so that we can effectively ignore the role of capital (i.e. non labor inputs) in the model and write the production function as $Q(L[E_m, E_f])$. Here L is a composite of male and female employment (E_m, E_f). Therefore, to see how the labor supply elasticity of a firm affects the wage that it pays, consider a profit maximizing firm that faces the following objective function:

$$Max\ \pi_{w_M, w_F} = pQ(E_m, E_f) - w_m E_m(w_m) - w_f E_f(w_f) \tag{2}$$

where p is the price of the output produced according to the production function Q, w_m and w_f are wages for male and female workers, respectively, which determine the male and female labor supplied to the firm (E_m and E_f) respectively. Taking the first order conditions:

$$\frac{\partial \pi}{\partial w_m} = p\frac{\partial Q(E_m, E_f)}{\partial E_m} * \frac{\partial E_m}{\partial w_m} - E_m(w_m)\frac{\partial E_m}{\partial w_m} = 0 \tag{3}$$

$$\frac{\partial \pi}{\partial w_f} = p\frac{\partial Q(E_m, E_f)}{\partial E_f} * \frac{\partial E_f}{\partial w_f} - E_f(w_f)\frac{\partial E_f}{\partial w_f} = 0 \tag{4}$$

and defining $\varepsilon_m = \frac{w_m}{E_m}\frac{\partial E_m}{\partial w_m}$ and $\varepsilon_f = \frac{w_f}{E_f}\frac{\partial E_f}{\partial w_f}$ as the labor supply elasticities of male and female workers, respectively, these equations can be written as:

$$p\frac{\partial Q(E_m, E_f)}{\partial E_m} = w_m\left(1 + \frac{1}{\varepsilon_m}\right)$$

$$p\frac{\partial Q(E_m, E_f)}{\partial E_f} = w_f\left(1 + \frac{1}{\varepsilon_f}\right)$$

By reorganizing the terms, we obtain:

$$w_m = \frac{p\frac{\partial Q(E_m, E_f)}{\partial E_m}}{\left(1 + \frac{1}{\varepsilon_m}\right)} \tag{5}$$

$$w_f = \frac{p\frac{\partial Q(E_m, E_f)}{\partial E_f}}{\left(1 + \frac{1}{\varepsilon_f}\right)} \tag{6}$$

From equations(5) and (6), we can derive the standard result of perfect competition ($\varepsilon = \infty$), where wages are equal to the marginal product of labor.

Finally, for two workers with identical marginal product of labor (i.e. $\frac{\partial Q(E_m,E_f)}{\partial E_f} = \frac{\partial Q(E_m,E_f)}{\partial E_m}$), we can obtain the gender wage gap (female to male wage ratio) as follows:

$$\frac{w_f}{w_m} = \frac{\left(1 + \frac{1}{\varepsilon_m}\right)}{\left(1 + \frac{1}{\varepsilon_f}\right)} \tag{7}$$

From equation (7), shows that a gender wage gap will be generated by differences in female and male firm labor supply elasticities.

4 Empirical Strategy

4.1 Estimating the Elasticity of Labor Supply

To estimate the labor supply elasticity to the firm, we followed Manning (2003) and used a simple model of an economy with search frictions. This model is in turn based on Burdett and Mortensen's (1998) seminal paper. These authors developed a model of an economy with on the job search, where employers post wages based on the behavior of their competitors. In this model, workers will switch jobs if they receive a higher wage elsewhere. For simplicity, we do not consider non-pecuniary benefits in the model.

Assume that there are M_t equally productive workers, where productivity is given by p, and each worker gains utility b from leisure. Furthermore, assume that there are M_e constant returns to scale firms, which are infinitesimally small compared to the entire economy. A firm set wages w to maximize steady-state profits $\pi = (p - w)L(w)$ where $L(w)$ is the labor supply to the firm. Let us also define $F(w)$ as the cdf of wage offers observed in the economy and $f(w)$ as the corresponding pdf. All workers in a firm must be paid identical wages. In this model, employed workers will accept a wage offer $w\acute{}$ if it is greater than their current wage w and nonemployed workers will accept $w\acute{}$ if $w\acute{} > b$.

Wage offers are randomly drawn from distribution $F(w)$, and arrive to all workers at rate λ. Assume an exogenous job destruction rate (δ) and that all workers leave the job market at rate (δ) to be replaced in nonemployment by an equivalent number of workers. Denote $R(w)$ and $s(w)$ as the recruitment flow and separation rate functions of a firm that pays a wage w , respectively:

$$R(w) = R^N + \lambda \int_0^W f(x)L(x)dx \tag{8}$$

$$s(w) = \delta + \lambda(1 - F(w)) \tag{9}$$

where R^N are the recruits from nonemployment. Burdett and Mortensen (1998) and Manning (2003) show that wage dispersion is an equilibrium outcome in this model, even when workers are equally productive, as long as one assumes that the arrival rate of job offers is positive but finite. In perfect competition, the arrival rate tends to infinity, and the wage will be the marginal product of labor. Meanwhile, if λ tends to zero, the wage will be the reservation wage b.

As Manning (2003) showed, it is possible to formulate the supply of labor to a firm with the following equation:

$$L_t(w) = L_{t-1}(w)\left[1 - s_{t-1}(w)\right] + R_{t-1}(w) \tag{10}$$

which can be read as follows: the labor supply today is equal to the sum of the fraction of workers from the last period who stay with the firm and the new recruits. Assuming a steady state we can rewrite equation (10) as:

$$L(w) = \frac{R(w)}{s(w)} \tag{11}$$

Taking the natural log of each side, multiplying by w and differentiating, we can write the labor supply elasticity at time t as a function of the long run elasticities of recruitment and separations:

$$\varepsilon_L = \varepsilon_R - \varepsilon_S$$

It is possible to further decompose these elasticities. Following Manning (2003), we can split the recruitment flow from unemployment versus recruitment flow from other firms and separation rate to unemployment versus separation rate to other employment:

$$\varepsilon_L = \theta^R \varepsilon_R^E + (1 - \theta^R)\varepsilon_R^N - \theta^S \varepsilon_S^E - (1 - \theta^S)\varepsilon_S^N \tag{12}$$

where ε_R^E is the elasticity of recruitment of workers from employment, ε_R^N is the elasticity of recruitment of workers from nonemployment, ε_S^E is the elasticity of separation of workers to employment, ε_S^N is the elasticity of separation of workers to nonemployment. θ^R and θ^S are the share of recruits from employment and share of separations to employment, respectively.

As discussed in the literature, the two separation elasticities can be easily estimated with duration models (described below). However, recruitment elasticities are more difficult to obtain (see details in Manning 2003, chapter 4). Therefore, recruitment elasticities can be expressed as functions of estimable quantities such as (see derivation in Manning (2003) chapter 4):

$$\varepsilon_R^E = \frac{-\theta^S \varepsilon_S^E}{\theta^R} \tag{13}$$

$$\varepsilon_R^N = \varepsilon_R^E - \frac{w\theta^{R}(w)}{\theta^R(w)\left[1-\theta^R(w)\right]} \tag{14}$$

This equation is derived from the definition of the share of total recruits from employment: $\left(\theta^R = \frac{R^E}{R^E+R^N}\right)$, where R^E and R^N are the recruits from employment and nonemployment, respectively. Taking the natural log of each side and differentiating yield equations (13) and (14). As presented in Webber (2016), the second term on the right hand side of equation (14) can be considered as the bargaining premium that an employee receives from searching while currently employed.

To conclude, the labor supply elasticity to the firm can be written as a function of both separation elasticities, the premium to searching while employed and the calculated shares of separations and recruits to/from employment.

4.1.1 Estimation of the Elasticity of labor supply to the firm

To estimate the labor supply elasticity to the firm by gender, we follow Webber (2016). This author used an augmented gender by firm level implementation of the methodology proposed in Manning (2003). To estimate the labor supply elasticity to the firm, we need several elements: First, the elasticities of separation to employment (ε_S^E) and nonemployment (ε_S^N). Second, the premium to searching while employed $\left(\frac{w\theta^{R}(w)}{\theta^R(w)\left[1-\theta^R(w)\right]}\right)$. Third, the recruitment and separation share for each firm (θ^S and θ^R). Each of the following models is run separately by gender for every firm in the sample, where the unit of observation is an employment spell.

We begin with the estimation of the elasticity of separation to nonemployment (ε_S^N). To do this, we use a Cox proportional hazard model given by:

$$\lambda(t \mid \beta^{N,\ sep}\ \log(earnings)_i + X_i\gamma^{N,\ sep}) = \lambda_0(t)e^{(\beta^{N,\ sep}\ \log(earnings)_i + X_i\gamma^{N,\ sep})} \tag{15}$$

where $\lambda()$ is the hazard function; λ_0 is the baseline hazard; t is the length of employment; $\log(earnings)$ is the natural log of monthly earnings of individual i and X is a vector of explanatory variables. Workers who transition to a new employer or are with the same employer at the end of the data series are considered to have a censored employment spell. β is the estimated elasticity of separation to nonemployment. The estimation of the elasticity of separation to employment (ε_S^E) follows an analogous setting:

$$\lambda(t \mid \beta^{E,\ sep}\ \log(earnings)_i + X_i\gamma^{E,\ sep}) = \lambda_0(t)e^{(\beta^{E,\ sep}\ \log(earnings)_i + X_i\gamma^{E,\ sep})} \tag{16}$$

with the only difference being that the sample is restricted to workers who do not have a job transition to nonemployment. β is the estimated elasticity of separation to employment.

To estimate the premium to searching while employed $\left(\frac{w\theta^R(w)}{\theta^R(w)\left[1-\theta^R(w)\right]}\right)$ we follow Manning (2003), who shows that it is equivalent to the coefficient on log earnings when estimating the following logistic regression:

$$P_{rec} = \frac{e^{(\beta^{E,\ rec}\ \log(earnings)_i + X_i\gamma^{E,\ rec})}}{1 + e^{(\beta^{E,\ rec}\ \log(earnings)_i + X_i\gamma^{E,\ rec})}} \tag{17}$$

The dependent variable takes a value of 1 if a worker was recruited from employment and 0 if she/he was recruited from nonemployment. This coefficient is interacted with time dummies to enable time variation. The same explanatory variables in the separation equations are used in this logistic regression. We present more details about these variables in the following section.[2]

The intuition is that a large (in absolute value) coefficient on the log earnings variable implies that a small increase in earnings of an individual will greatly decrease the probability of separating in any given period. With perfect competition in the labor market, we would expect this coefficient to be infinitely high. Meanwhile, in a more monopsonistic labor market, we would expect a smaller coefficient.

5 Data and Summary Statistics

To estimate the labor supply elasticity of the firm by gender, we use Chile's full administrative Unemployment Insurance ("Seguro de Cesantía", in Spanish) database provided by the Unemployment Fund Administrator.

[2] Each equation is also estimated with an indicator variable for whether the employment spell was in progress at the beginning of the data window to correct for potential bias of truncated records. Additionally, all models were re-estimated using only job spells, for which the entire job spell was observed, with no substantial differences observed between these models.

By law, the Unemployment Fund Administrator is required to collect all contributions to unemployment individual accounts for each labor relation on a monthly basis. The affiliation to the unemployment insurance is mandatory for all new contracts since 2002. For pre 2002 contracts, affiliation is voluntary.

Our dataset spans from January 2010 to June 2019. Thus, we consider employment spells that began in January 2010 or after. By 2010, 86% of the Chilean labor force were affiliated to the unemployment insurance system. Our dataset includes individual and employer characteristics such as age, age squared, education, gender, region, time of affiliation to the insurance, monthly taxable income, industry, date of hiring, type of contract, geographical location and firm size. The variable education has several missing observations in the Unemployment Insurance dataset; hence, we complemented it with administrative information from the Ministry of Education. Thus, we can recover the missing information of the education variable.

We only include an employment spell in the sample if it could be considered the dominant job at some point, which is defined as paying the highest wage of an individual's jobs in a given month. To obtain our final dataset, we removed all spells that spanned fewer than 3 months because the data do not contain information about when an individual was hired/separated during the month. Therefore, the entries for the first and last months of any employment spell will almost certainly underestimate the monthly earnings of an individual (unless the individual was hired on the first day or left employment on the last day of a month). Although this procedure certainly eliminates short (and likely low-wage) jobs, it prevents us from systematically underestimating monthly wages.[3] To avoid outliers, we removed job spells that fell in the top and bottom 1 % of earning observations. To estimate our model, we also limited our analysis to firms with at least 100 total employment spells of any length over the lifespan of the firm and 25 separations or hirings.

In our sample, we consider individuals with 18-64 and 18-59 years of age for men and women, respectively. These choices are made because the retirement age in Chile is 65 for men and 60 for women.[4] Transitions to employment are defined as those where after the end of an employment spell and in the following month, there is a new employment spell with a different employer. Transition to nonemployment is defined if there is no new employment spell in the following month after the end of the previous employment spell.

After making these restrictions, we have a sample of all workers for whom we can estimate a gender-specific labor-supply elasticity. This sample consists of 14,482,904 employment spells (10,005,698 and 4,477,206 employment spells for men and women, respectively), for 5,137,151 unique individuals who work at 8,777 separate firms.

[3] Relaxing this restriction does not significantly change the results.

[4] We also estimate our model with: i)18-60 and 18-55, ii) 25-64 and 25-59 and iii) 25-60 and 25-55 for men and women, respectively. The results do not significantly change.

In **Table 1**, we present the descriptive statistics of our database. We observe that on average, male workers are slightly older and less educated than female workers. Furthermore, male workers receive 30.4% higher monthly wages than female workers and have shorter employment spells than female workers (13.13 months versus 15.19 months on average). Firms in the sample have a monthly average of 204 and 409 men and women, respectively. The higher average for women is because in our sample firms that hire women are commonly larger than those that hire men. These firms are commonly classified as large firms, considering their number of employees. This result is consistent with the imposed data restrictions.[5] At the bottom part of **Table 1**, we observe some characteristics of the firms. On average they hired 13.7 and 18.8 men and women per month, respectively. When recruitment and separations are compared, we observe that the average employment growth rate per firm is 1.07 and 1.14 for men and women respectively.[6]

All restrictions to the data imposed in this section are identical to those imposed by Webber (2015 and 2016), except for the frequency of earning data because Webber only has quarterly earnings. We decided to use monthly earnings for our main estimation because the use of quarterly earnings implies the removal of all employment spells shorter than 3 quarters, which implies a relevant loss of data.[7] In subsection 6.5, we will reestimate our model using quarterly earnings data to properly compare our results with Webber. The other difference from Webber (2016) is that he uses ethnicity as one of his control variables and we do not use it, mainly due to data constraints. However, this should not be too problematic in our case because only approximately 13% of Chilean population belongs to a minority ethnic group.[8] Finally, a limitation of this study and Webber's is that neither include non-pecuniary benefits nor usual weekly working hours, which may be important to estimate the labor supply elasticities.[9]

6 Results

6.1 Labor Supply Elasticity by Firm and Gender

Columns 1-4 of **Table 2** report the average (weighted by employment) firm-level elasticities of recruitment from employment and nonemployment, and the separation elasticities to employment and nonemployment,

[5] At least 100 employment spells over the lifespan of the firm and 25 separations or hirings.

[6] Employment growth rate = $\frac{Recruitment}{Separations}$

[7] Webber used this frequency because his data did not contain information on when an individual was hired/separated during the quarter. Webber used data from the United States, which gave him a much larger sample size.

[8] There are no large differences by gender: 12.9% and 12.7% for men and women, respectively. Census 2017, Instituto Nacional de Estadisticas.

[9] However we do have information on weekly contractual hours, which may differ from usual working hours, but it would be at least helpful to compare men and women with identical ranges of weekly contractual hours. The results do not significantly change if we include weekly contractual hours or not. Also, results do not change significantly if we control for contractual full time hours (i.e. 45 hours a week). We decided not to include weekly contractual hours (or weekly contractual fulltime hours) in our main estimation because there are several missing values in this variable. We do not include working hours to make it comparable with Webber (2016) who also did not include hours.

respectively. Column 5 of **Table 2** lists the average (weighted by employment) firm-level elasticities broken down by gender, which is a combination of the first four columns and the recruitment and separation shares to/from employment as discussed in **section 4**. In the first three rows of **Table 2**, we present the long-run labor supply elasticities, while the fourth row describes the more flexible specification when a steady-state is not assumed, and elasticities are allowed to vary over time (i.e. the short run elasticity of Manning 2003). The preferred specification for the long run elasticity is row 3 which includes all control variables. Comparing rows three and four for men and women, we observe that the long run elasticities are slightly smaller than those obtained when we relax the steady-state assumption, but in all cases, men's elasticities are larger than women's elasticities. Because of space limitation and to use the more flexible model, our preferred specification is the model in row 4.

The labor supply elasticities are 0.61 for men and 0.36 for women. Using the main result of our theoretical model, given by equation (7), we find the empirical value of the gender wage gap, which implies that men should earn approximately 28% more than women due to the difference in labor supply elasticities *ceteris paribus*. This value represents approximately 90% of the raw gender wage gap from our sample. Thus the labor supply elasticities are small, which suggests that firms indeed retain relevant market power. A second relevant information from **Table 2,** is that the differences in gender labor supply elasticities appear to be explained by the differences in elasticities to/from nonemployment. In particular, the largest difference occurs in the elasticity of recruitment from nonemployment.

6.2 Distribution of Labor Supply Elasticity by Firm and Gender

Now, we analyze the differences of between and within firm percentile elasticity distribution. Columns 2-5 of **Table 3** list results for the 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of the distribution of estimated firm-level labor supply elasticities. The result presented in column 1 is larger than those in columns 3, which implies that the mean is higher than the median. This finding is consistent with a right-skewed distribution of estimated elasticities, where elasticities reach 1.68 and 1.34 for men and women, respectively at the 90^{th} percentile, which are approximately 3 and 4 times the mean elasticity of each gender. Thus, elasticities up to the 90^{th} percentile remain notably low, which suggests that there is considerable monopsony power in the Chilean labor market.

A second interesting result is that the differences across firm percentiles in the elasticity gap are larger than differences within firm percentiles. For example, the within elasticity gap in the 90^{th} percentile is 0.34 (i.e. 1.68 and 1.43 for men and women, respectively). This difference is much smaller than 1.63 and 1.21

obtained for the 90^{th}- 25^{th} percentile for men and women, respectively. Furthermore, we observe that at the 25^{th} percentile, the labor supply elasticity of men is smaller than that of women. However, the elasticity gap reverses as we move up throughout the elasticity distribution. To gain insights into the characteristics of firms that appear at the lowest and highest parts of the elasticity distribution, we present in **Table 4** a characterization of firms in the lower 25^{th} and upper 75^{th} percentile of the labor supply elasticity distribution. For men and women, firms with low labor supply elasticities (25^{th} percentile) pay slightly lower wages and have shorter employment spells than firms with high elasticity (75^{th} percentile). Furthermore, on average, firms with low labor supply elasticity have slightly younger workers than firms with high elasticity. Finally, workers in firms with low labor supply elasticity have lower education than those working in firms with high labor supply elasticity.

6.3 Between and Within Firm Differences

We conducted a complementary analysis to further investigate between versus within firm differences in gender-specific elasticities. For this analysis, we used a sample of firms that only included individuals who worked at firms where we could estimate the labor-supply elasticities of both men and women. This sample contains 9,763,004 employment spells, which belongs to 4,210,726 unique individuals, who work at 4,360 separate firms**.**

In the upper panel of **Table 5**, we calculate the difference among these gender-specific elasticities, which suggests that in our preferred model (full model time varying), on average, male elasticities between firms are 0.14 higher than female elasticities. In the second panel of **Table 5**, we present within firm differences, which are calculated by taking the difference between male and female elasticities for each firm and then taking the average of the differences across firms. The results of our preferred model (full model time varying) suggest that, on average, male elasticities are 0.14 higher than female elasticities within firms. Thus, between and within firm differences are similar in the short term. However, using our preferred long run model (i.e. full model), we observe that between firm differences are higher than within firm differences (0.12 versus 0.08).

6.4 Labor Supply Elasticity by Industry

We also analyzed the labor supply elasticities of men and women by industry. In **Table 6**, we observe that for most industries, the elasticity of labor supply of men at the firm level is larger than that of women. Only in educational services, women have more elastic labor supply elasticities than men. Furthermore, this industry has the lowest magnitudes of labor supply elasticity, which suggests that schools have a relevant labor market power. Another interesting result is that there is an important variation of elasticities of 0.17

- 0.93 for men and 0.23 - 0.8 for women. For men, the more elastic industries (i.e. the more competitive industry) are manufacturing and mining; for woman, the more elastic industries are financial intermediation, transportation and storage. Despite differences in magnitude (discussed below), it is interesting that Webber (2016) also finds that manufacturing and mining are the two most competitive industries in the United States for men. For women, transportation is among the two most competitive industries in Chile and the United States. The least competitive industries in Chile for both men and women, are educational services and administrative services and support, which are also among the least competitive industries in the United States. Finally, the greatest elasticity differential can be found in mining, where men have an elasticity of 0.83 compared to 0.37 for women. Some of these differences may be due to differences in occupation within each industry classification; unfortunately, our data do not enable the identification of occupation.

6.5 Labor Supply Elasticities in Developed versus Developing Countries

Having obtained these estimates, one wonders if they are in line with those obtained for other countries with different or similar characteristics. Previous studies of the labor supply elasticity under dynamic monopsony models for Norway, Italy and Australia found elasticities of 0.3-1.4, and the labor supply elasticities of men (0.4 - 1.4) are always higher than those of women (0.3 - 1.1). However, these studies are not directly comparable to our estimation due to differences in frequency of data, data source (survey versus administrative data) and methodology.[10] Furthermore, all evidence estimated labor supply elasticities at the market level. The only study that estimated labor supply elasticities at the firm level with administrative data (as in our case) was Webber (2016).

Webber's work reported the labor supply elasticities at the firm level for the United States using the same methodology and restrictions as those imposed here. The only difference is the frequency of earnings data; Webber used quarterly earnings, and we have been using monthly earnings. To properly compare both studies, we reestimate our model with quarterly earnings as conducted in Webber (2016). We found that our estimated previous elasticities increased for men and women. In **Table 7**, the labor supply elasticity increases from 0.61 to 0.70 for men and from 0.36 to 0.50 for women. Despite the increase in magnitude, they are still small, which suggests some degree of labor market power by the firms.

We compared our re-estimated results with those obtained by Webber for the United States. The results in **Table 7** suggest that the labor supply elasticities for the United States are higher than those estimated for Chile. As expected, this fact suggests fact would suggests that the United States has a more competitive

[10] For example: in the Chilean and Italian case, monthly wages from administrative sources were used, while in the Australian case, the authors used yearly wages. For Norway, daily wages were used (see Barth and Dale-Olsen 2009, Booth and Katic 2011, Sulis 2011).

labor market. In particular, for men, the elasticity in the United States is 1.09, which is higher than the Chilean equivalent (0.70). For women, the difference is larger; the elasticity is 0.94 for the United States and 0.50 for Chile. This comparison is interesting because the Chilean labor market has important differences compared with the United States labor market. For example, the Chilean labor market has a higher level of informality (30%) than the United States labor market (20%)[11], lower levels of average education (10.3 years versus 13.4 years)[12], greater difficulty associated with starting a business (56^{th} versus $8^{\mathbf{th}}$ in Doing Business Ranking 2019), less investment in transport infrastructure (34% of Chilean GDP and 42% of United States GDP)[13] and an overall higher rigidity of the labor market (e.g. higher severance payments, higher unionization rate, etc.)[14] which highlights important differences between developed versus developing labor markets. For example, Chilean women working in the informal sector (or not working at all) have access to free public childcare, while they do not have it in United States. Then, with an identical raise in wages, it would be more costly to lift a women from nonemployment in Chile than in the United States, ceteris paribus. This issue affects the elasticity of recruitment from nonemployment for women, which affects the overall labor supply elasticity of women in Chile. This may be one of many potential reasons why Chilean women have a much lower labor supply elasticity than women in the US. This would be an interesting avenue for future research.

Therefore, our results suggest that the labor supply elasticities from Chile (0.70 and 0.50 for men and women, respectively) appear to be more inelastic than those obtained for the U.S. and located at the middle and lower bounds of the range of elasticities for men and women, respectively, compared to the results of several empirical studies for different developed countries such as Australia, Italy and Norway (0.3 - 1.4). With the elasticities obtained here (0.7 and 0.5), men should earn approximately 19% more than women due to the difference in labor supply elasticities *ceteris paribus*. The difference in labor supply elasticities theoretically explains approximately 2/3 of the raw gender wage gap of our data, which is higher than the approximately 1/3 reported for the United States by Webber.

[11] Chile: Instituto Nacional de Estadísticas. U.S.A.: Federal Reserve Bank of Saint Louis: https://www.stlouisfed.org/on-the-economy/2017/april/informal-labor-market

[12] Source: Human Development Reports. http://hdr.undp.org/en/indicators/103006

[13] OECD: https://data.oecd.org/transport/infrastructure-investment.htm

[14] In the OECD index (2013), where 0 is soft and 5 is strict, Chile has a score of 2.5 for individual dismissal while the U.S. has 0.5. Source: https://www.oecd.org/employment/emp/oecdindicatorsofemploymentprotection.htm

https://www1.compareyourcountry.org/employment-protection-legislation/en/0/176/datatable//CHL+USA

The unionization rate in 2018 is 20% in Chile and 10.5% in the United States. Source: for Chile, Consejo Superior Laboral. For the U.S., https://www.bls.gov/news.release/pdf/union2.pdf

7 Concluding Remarks and Policy Recommendations

We analyzed the gender wage gap using a dynamic monopsony model and estimated labor supply elasticities at the firm level for Chile. We find that depending on the specification, Chilean men earn approximately 19% - 28% more than women because of the difference in labor supply elasticities, *ceteris paribus*. Our results also suggest that the labor supply elasticities are small, which implies that firms have relevant market power. Firms with low labor supply elasticities have slightly younger and less educated workers, pay lower wages and have shorter employment spells than firms with high labor supply elasticities. Furthermore, we find that the differences in gender labor supply elasticities appear to be explained by the differences in elasticities to/from nonemployment. In particular, the biggest difference occurs in the elasticity of recruitment from nonemployment. An interpretation of this finding can be that increased search frictions for women affect their recruitment from nonemployment. Thus, there may be frictions that are sticking them to their nonemployment status (or at least non formal employment). Potential explanations for this result may be that informality is more attractive in Chile due to for example, the lack of childcare coverage for a relevant proportion of employed women (and free childcare for non-employed women in Chile), nonpecuniary benefits, specific preferences, bargain power or maybe even cultural issues regarding the role of women in Chilean society. For example, the current Chilean labor code establishes that "every firm with 20 or more female workers, regardless of their age and marital status, has to provide childcare facilities within firm premises so that mothers can feed their children and leave them there while working". Hence, all women working in firms with fewer than 20 female workers do not have childcare provision. This situation contrasts with the free public childcare provision for the most vulnerable population, which includes non employed women and women working in the informal sector. Thus, childcare regulation can be one of several determinants of the low elasticity of recuitment from nonemployment of women in Chile.

Furthermore, reestimating our model using quarterly earnings data, to properly compare our results with Webber (2016) and using the same methodology, we compared Chilean labor supply elasticities with those of the United States. As expected, our results suggest a much less competitive labor market for the middle-income country (Chile) than for the high-income country (United States). Furthermore, the elasticity of Chilean men is not far from the intermediate values obtained in the literature; however, the elasticity of women appears to be notably low compared to international evidence. Again, as expected, the main driver for the low labor supply elasticity of Chilean women appears to be the elasticity of recruitment from nonemployment. Thus, there are some determinants that affect the stickiness of women to nonemployment. As previously mentioned, several determinants should be more comprehensively investigated in future research. *While these hypotheses must be further explored, it becomes clear that a policy recommendation for* *the Chilean case is to go beyond salary incentives to attract women into the labor market. For example,* one policy that can encourage women to start working in the formal sector is a better provision of childcare in the private sector.

We also investigated *between-* versus *within-*firm differences in gender-specific elasticities. Our results suggest that in the short run, there is no significant differences between and within firms. However, in the long run, between-firm differences are higher than within-firm differences. In other words, in the long run, between-firm differences in elasticities are more important than within-firm differences in elasticities. An important policy recommendation that transpires from this result is that regulations targeted at firms may be able to help address the gender gap. These results also suggest that the gender wage gap appears to be driven more by *structural factors* that generate gender sorting to firms, especially in the long run. For example, women may sort themselves more into some industries or firms where the labor supply elasticity is low. This phenomenon can be due to various reasons such as education, preferences and culture, among others. *Our results call for public policies that focus on structural factors such as early determinants of gender sorting by firms. We think that these results are important and should be considered when designing policies to decrease the gender wage gap, especially in the context of developing countries.* This result is consistent with Card et al. (2016) and Cruz and Rau (2017), who analyzed Portuguese and Chilean data, respectively, used different approaches and found that most of the wage gap was explained mostly by sorting instead of bargaining power within firms, which played a comparatively smaller role.

We also studied the gender labor supply elasticity by industry. Our results suggest that despite the differences between Chilean and American labor markets, manufacturing and mining appear to be the most competitive sectors in both countries for men, and transportation is among the most competitive sectors in both countries for women. Meanwhile, educational services and administrative services and support are among the least competitive industries in both countries for men and women. Finally, we propose that this type of analysis should be replicated in other middle-income and lower-income countries to gain a more in-depth understanding of the role of market power in the gender wage gap in labor markets with different characteristics.

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Appendix

Table 1

Descriptive Statistics

	Male		Female	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Unit of Observation: Employment Spell	(1)	(2)	(3)	(4)
Age (Years)	35.5	11.9	34.1	11.2
< High School	0.32	0.24	0.26	0.23
High School Diploma	0.38	0.49	0.34	0.47
Some College	0.21	0.40	0.26	0.44
College Degree+	0.09	0.14	0.14	0.19
Spell Duration	13.13	17.04	15.19	19.34
Wages (CL$)	630,104	460,969	482,853	383,148
Wages (US$)	768	562	589	467
Observations	10,005,698		4,477,206	
Unit of Observation: Firm				
Average Hires / month	13.71	48.28	18.81	70.08
Employment Growth Rate	1.07	1.28	1.14	1.30
Firm Employment	204	621	409	968
Observations	8,777			

Note: Summary statistics by gender of our final sample from the "Seguro de Cesantía" administrative records complemented with the administrative records from the Ministry of Education. The wages and employment spells are presented in monthly terms. The employment growth rate is defined as recruitment/separations. Exchange Rate= CL$820 / US$.

Table 2

Firm Level Labor Supply Elasticity

Model	ε_r^e	ε_r^n	ε_s^e	ε_s^n	Elasticity
	(1)	(2)	(3)	(4)	(5)
Male Elasticities					
Earnings only	0.50	0.20	-0.50	-0.71	0.93
No education controls	0.39	0.14	-0.39	-0.35	0.56
Full model	0.40	0.11	-0.40	-0.36	0.54
Full model time varying	0.45	0.15	-0.45	-0.37	0.61
Female Elasticities					
Earnings only	0.47	0.05	-0.47	-0.70	0.70
No education controls	0.37	0.06	-0.37	-0.31	0.33
Full model	0.38	0.09	-0.38	-0.31	0.31
Full model time varying	0.40	0.04	-0.40	-0.31	0.36

The first row represents estimates from equations (15)–(17) where the only regressor in each model is log earnings. The second row also includes: age; age-squared; region, type of contract, number of employees working at the firm and industry indicator variables. The third row includes all previous controls and indicator variables for education level. The first four columns report the average firm-level elasticities of recruitment from employment (ε_r^e) and nonemployment (ε_r^n) and the separation elasticities to employment (ε_s^e) and nonemployment (ε_s^n). The final column combines these elasticities with the calculated shares of separations/recruits to/from employment and separation rates to obtain the labor supply elasticity. The first three rows only report the long-run elasticities, while the fourth row describes the elasticities when a steady-state is not assumed, and they are allowed to vary over time (i.e. the short run elasticity of Manning 2003).

Table 3

Estimated Firm-level Labor Supply Elasticities and Their Distribution

Model	Mean	25^{th}	50^{th}	75^{th}	90^{th}
	(1)	(2)	(3)	(4)	(5)
Male Elasticities					
Earnings only	0.93	0.48	0.87	1.29	1.80
No education controls	0.56	0.15	0.51	0.88	1.35
Full model	0.54	0.13	0.47	0.88	1.40
Full model time varying	0.61	0.05	0.50	1.06	1.68
Female Elasticities					
Earnings only	0.70	0.31	0.68	1.12	1.44
No education controls	0.33	0.01	0.27	0.71	1.04
Full model	0.31	0.04	0.24	0.69	1.05
Full model time varying	0.36	0.13	0.34	0.87	1.34

Three separate regressions, which correspond to equations (15)–(17), were separately estimated by gender for each firm in the data that satisfied the conditions described in the Data section. The coefficients on log earnings in each regression were combined, weighted by the share of recruits and separations to employment to obtain the estimate of the labor supply elasticity to the firm. The first row of each panel represents estimates from equations where the only regressor in each model is the log earnings. The second row also includes: age; age-squared;, region, type of contract, number of employees working at the firm and industry indicator variables. Third row includes all previous controls and indicator variables for education level. Year effects are included in all models. The first three rows report only the long-run elasticities, while the fourth row describes the elasticities when a steady-state is not assumed, and they are allowed to vary over time (i.e. the short run elasticity of Manning (2003)).

Table 4

Characterization of Firms by Elasticity Percentile

Model	Full Model Time Varying 25^{th}	75^{th}
	(1)	(2)
Male Elasticities		
Age	35.55	35.58
<High School	0.33	0.31
High school diploma	0.38	0.37
Some college	0.20	0.20
College degree +	0.09	0.12
spell	13.01	14.09
Log(wage)	13.06	13.10
Female Elasticities		
Age	34.76	34.81
<High School	0.29	0.28
High school diploma	0.35	0.34
Some college	0.23	0.24
College degree +	0.13	0.14
spell	14.13	15.28
Log(wage)	12.82	12.92

Columns report the 25^{th} and the 75^{th} percentile of the labor-supply elasticity distribution calculated using only the full model time varying results. The full model time varying describes the elasticity when a steady-state is not assumed, and they are allowed to vary over time (i.e. the short run elasticity of Manning (2003)).

Table 5

Differences in labor Supply Elasticities (between and within firms)

	Mean
Differences Between Firms	
Earnings only	0.13
No education controls	0.14
Full model	0.12
Full model time varying	0.14
Differences Within Firms	
Earnings only	0.13
No education controls	0.08
Full model	0.08
Full model time varying	0.14

Note: Between firms differences among men and women are obtained using firms that only include individuals who work at the firms, where we could estimate both male and female labor-supply elasticities. We take the average male elasticity between firms and substract the average female elasticity between firms. Within firms differences are obtained by taking the difference between male and female elasticities for each firm and then taking the average of the differences across firms. The sample includes workers who work at firms where we can identify both a male and female elasticity. This sample has 9,763,004 employment spells, which belongs to 4,210,726 unique individuals, who work at 4,360 separate firms.

Table 6

Average firm labor supply elasticity by industry

Variable	Men	Women
Agriculture	0.54	0.23
Mining	0.83	0.37
Manufacturing	0.93	0.59
Electricity, Gas and Water	0.54	0.32
Construction	0.51	0.41
Retail	0.58	0.29
Transportation and Storage	0.67	0.67
Accommodation and Food Services	0.46	0.26
Information and Communications	0.68	0.51
Financial Intermediation and insurance	0.82	0.80
Professional, scientific and technical services	0.43	0.37
Administrative Services and Support	0.44	0.23
Educational Services	0.17	0.24
Health Care and Social Services	0.73	0.58

We present the full model time varying results only. The full model time varying describes the elasticity when a steady-state is not assumed, and they are allowed to vary over time (i.e. the short run elasticity of Manning (2003)).

Table 7

Comparing Developed versus Developing Labor Supply Elasticities

Model	Chile	U.S.
	(1)	(2)
Male Elasticities		
Full model time varying	0.70	1.09
Female Elasticities		
Full model time varying	0.50	0.94

The first row of each panel represents estimates from equations (15)–(17), where the control variables include: log quarterly earnings; age; age-squared, region, type of contract, number of employees working at the firm and industry indicator variables; indicator variables for education level and year effects. Both columns represent the elasticity at the mean of the distribution for the full model time varying. The results for other specifications are available upon request. The full model time varying describes the elasticity when a steady-state is not assumed, and they are allowed to vary over time (i.e. the short run elasticity of Manning (2003)).