Gender Wage Gap and FirmsíDynamic Monopsony: Voluntary versus Involuntary Separations

Sanchez, Rafael and Finot, Javier and Villena, Mauricio G.

Ministerio de Hacienda, Chile, Ministerio de Hacienda, Chile, Escuela de Negocios, Universidad Adolfo Ibáñez, Chile

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Rafael Sánchez * Javier Finot† Mauricio G. Villena‡

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Abstract

We exploit a national administrative dataset to estimate labor supply elasticities at the firm level, distinguishing for the first time the source of separation (quits versus layoffs), which is crucial as only the former is consistent with employees' responses to changes in wages. Our results suggest that labor supply elasticities increase by around 18% when all separations (i.e., without identifying its source) are used instead of voluntary separations (i.e., quits). Hence, it transpires that previous literature, which due to data constraints, did not identify the source of separations, presented results which were upward biased, thus overestimating labor market competitiveness. We also find that between firm differences in the gender-specific elasticities are more relevant than within firm differences when voluntary separations are used, a result that should be considered by governments in the design of their gender gap policy agenda.

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

*Corresponding Author: Rafael Sánchez, Universidad Adolfo Ibáñez and Chilean Ministry of Finance. Teatinos 120, Piso 12. Santiago, Chile. Email: rsanchez@hacienda.cl.

†Chilean Ministry of Finance.

‡Universidad Adolfo Ibáñez and Chilean Ministry of Finance.

1 Introduction

Traditionally, the available literature has focused on studying the existence of discriminatory wage differences in perfectly competitive labor markets which assumes a perfectly elastic labor supply (Becker 1971). Related literature has questioned Becker's approach, suggesting that monopsonistic power on the part of the employer in the labor market (Robinson 1969, Madden 1973, Black 1995, Manning 2003) can explain discriminatory behavior due to the existence of frictions in the labor market. In particular, monopsony models could explain how discriminatory gender wage differences arise and persist if firms wield greater monopsony power over female than male workers. For this to hold, women's supply of labor to the firm must be less wage elastic than men's.

Due to data constraints, some studies have only recently started to consider the impact that imperfect competition in the labor market might have on the gender wage gap. Most of these analyses have been done at the market level and using wage-separations elasticities (although they recognize that it is more appropriate to use the wage–quit elasticity, but they do not have that information). These studies found that male elasticity is higher than females' elasticity and that this difference can explain around one third of the gender wage gap [Ransom and Oaxaca (2010) for the US. and Hirsch et al. (2010) for Germany].

Webber (2016) extended the theoretical and empirical model to the firm level. Webber estimated the male and female labor supply elasticity by firm and used them to study the gender pay gap for the U.S.. As in previous literature, Webber do not identify the reason of separations. He detects substantial search frictions in the U.S. labor market, with females facing a higher level of frictions than males. Vick (2017) points out that inclusion of layoffs in the data might confuse estimates based on worker movements, thus knowing the reason for job separations is critical, as elasticity estimates based on hazard models of quits vs. layoffs produce very different wage coefficients. In particular, he estimates the elasticity at the market level and finds that elasticities using separations move in a different direction than quit elasticities.

We contribute to recent dynamic monopsony models and the gender gap literature by adding some key elements. First, to the best of our knowledge, we are the first study to estimate male and female labor supply elasticities at the firm level using the reason for job separation. We show that identification of the cause of separation is crucial as our results suggest that by using voluntary separations, labor markets appear to be more monopsonistic versus estimations obtained without identification of the source of separation, suggesting an upward bias in the extant literature. Second, to our knowledge, we are the first study that has attempted to measure monopsony power at the firm level in middle income countries. This is relevant as the only existing evidence at the firm level comes from the U.S., and it can be argued that market imperfections (i.e., search frictions, mobility costs, etc) are more prevalent in developing countries due to higher poverty rates, greater difficulty in starting businesses, poorer information technologies and transportation infrastructure, fewer education opportunities, and lower unionization rates than in the U.S.. Additionally, some empirical literature notes that larger informal sectors and more widespread discrimination in many middle income countries are especially harmful to female equality and mobility (Chioda 2011;World Bank 2012).

2 Empirical Strategy

To estimate the labor supply elasticity to the firm, we use a simple model of an economy with search frictions as in Manning (2003) and Weber (2016). Following these, the labor supply elasticity at the firm level can be expressed as:

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

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 the share of separations to employment respectively.

As discussed in the literature, the two separations elasticities can be easily estimated with duration models (described below). However, recruitment elasticities are harder to obtain (see details in Manning 2003, chapter 4). Thus, it is handy to express recruitment elasticities as functions of estimable quantities (see derivation in Manning (2003) chapter 4):

$$\varepsilon_R^E = \frac{-\theta^S \varepsilon_S^E}{\theta^R} \tag{2}$$

$$\varepsilon_R^N = \varepsilon_R^E - \frac{w\theta^R(w)}{\theta^R(w)\left[1-\theta^R(w)\right]} \tag{3}$$

This is derived from the definition of the share of total recruits which come 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 non-employment respectively. Taking the natural log of each side and differentiating yields equations (2) and (3). As presented in Webber (2016), the second term of the right hand side of equation (3) can be thought of as the bargaining premium that an employee receives from searching while currently employed.

2.1 Estimation of the Elasticity of labor supply to the firm

To estimate the labor supply elasticity to the firm level by gender, we follow Webber (2016), who begins 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:

$$\lambda(t \mid \beta^{N,\ sep}\ \log(earnings)_i + X_i\gamma^{N,\ sep}) = \lambda_0(t)e^{(\beta^{N,\ sep}\ \log(earnings)_i + X_i\gamma^{N,\ sep})} \tag{4}$$

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 individual i's earnings and X is a vector of explanatory variables. Workers who transition to a new employer or who are with the same employer at the end of the data series are considered to have a censored employment spell. β represents the estimate of the elasticity of separation to nonemployment.

The estimation of the elasticity of separation to employment (ε_S^E) follows an analogous setting:

$$\lambda(t \mid \beta^{E,\ sep}\ \log(earnings)_i + X_i\gamma^{E,\ sep}) = \lambda_0(t)e^{(\beta^{E,\ sep}\ \log(earnings)_i + X_i\gamma^{E,\ sep})} \tag{5}$$

with the only difference being that the sample is restricted to those workers who do not have a job transition to nonemployment. 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 this is equivalent to the coefficient on log earnings when estimating the following logistic regression:

$$P_{rec} = \frac{e^{(\beta^{E,\ rec}\ \log(earnings)_i + X_i\gamma^{E,\ rec})}}{1 + e^{(\beta^{E,\ rec}\ \log(earnings)_i + X_i\gamma^{E,\ rec})}} \tag{6}$$

where the dependent variable takes a value of 1 if a worker was recruited from employment and 0 if they were recruited from nonemployment. This coefficient also interacts with time dummies to allow time variation.

3 Data and Summary Statistics

To estimate the labor supply elasticity of the firm by gender, we use the full administrative Unemployment Insurance ("Seguro de Cesantía", in Spanish) database provided by the Unemployment Fund Administrator. By law, the Unemployment Fund Administrator is required to collect, on a monthly basis, all contributions to unemployment individual accounts for each labor relation. To obtain our final dataset, we removed all spells that span fewer than 3 months, because the data do not contain information on when during the month an individual was hired/separated, thus the entries for the first and last month of any employment spell will almost certainly underestimate the monthly earnings rate (unless the individual was hired on the first day or left employment on the last day of a month). While this certainly eliminates short (and likely low-wage) jobs, it also prevents us from systematically underestimating monthly wages.[1] We also removed job spells that fell in the top and bottom 1 % of earnings observations. We also limit 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. Finally, we also exclude firms in the agricultural sector.

The time span covered in our dataset goes from January 2010 to December 2017 and includes individual and employer characteristics such as age, age squared, education, gender, tenure, tenure squared, region, time of affliation to the insurance, monthly taxable income, the reason and date of separation, industry, date of hiring, type of contract and geographical location, among others.

The variable education has several missing observations in the Unemployment Insurance dataset which is why we complemented it with administrative information from the Ministry of Education. In this way, we can recover the missing information of the education variable. From information included in the online appendix (descriptive statistics), we observe that male workers are slightly older and less educated than female workers. Furthermore, male workers receive 34.4% higher wages than female workers and also have shorter employment spells than female workers (17.7 months versus 20.4 months on average).

After making these restrictions, we are left with a sample of all workers for whom we can estimate a gender-specific labor-supply elasticity. This sample is made up of roughly 6,866,636 employment spells, belonging to about 3,212,361 unique individuals, who work at 7,357 separate firms.

4 Results

4.1 Labor Supply Elasticity by Firm and Gender

Column 1 of **Table 1** reports the average (weighted by employment) firm level elasticities using voluntary and all separations broken down by gender. It can be seen that labor supply elasticities are small (i.e. 0.56 for men and 0.45 for women in our full time varying model) suggesting a significant market power for firms in Chile. Our results are lower than those obtained by Weber (2016) for the U.S. (1.09 for men and 0.94 for women) with the same methodology, suggesting that Chilean labor markets are less competitive than the American labor market. For Chile, men should earn approximately 16% more than women as a result of

[1] Results do not change in a significant way with this assumption.

the difference in labor supply elasticities ceteris paribus. [2] This difference corresponds to 52.6% of the raw earnings gap in our data.

We re-estimate the same model but now using voluntary separations only (i.e. quits). Results are presented in column 5 of **Table 1** and suggest that elasticities decrease when only quits are used (0.49 for men and 0.38 for women). This result implies that men should earn approximately 19% more than women as a result of the difference in labor supply elasticities *ceteris paribus* (with all separations was 16%).This means that using voluntary separations instead of all separations increases by almost 19% the theoretical wage gap explained by the elasticity gap, reinforcing the relevance of identifying the cause of termination of the labor relation.

Despite that using voluntary separations greatly increases the percentage of the theoretical earning gap explained, elasticities are rather small suggesting that firms still do have relevant market power.These results cannot be compared against the findings of the previous literature, since we are the first to estimate it. Vick (2017) calculated this, but only at the market level, and he concluded that signs change when quits were used. In our case we find that there is no change of signs, although there is an important change in magnitude.

Comparing voluntary versus all separations results highlights the need to identify the nature of separations. Such distinction helps interpret the meaning of regression coefficients, especially in labor markets where quits are a small proportion of separations, as in Chile (approximately 15%**).** Failure to distinguish the two potentially biases elasticity estimates away from zero and might fail to capture gender differences in worker separation decisions.

4.2 Distribution of Labor Supply Elasticity by Firm and Gender

Now we turn to analyze the differences between and within firms. Results are presented in **Table 1** for both cases (all separations and voluntary separations). Columns 2, 3 and 4 present results for the 25^{th}, 50^{th} and 75^{th} percentiles of the distribution of estimated firm level labor supply elasticities. It can be noted that the results presented in columns 1 and 5 are larger than those presented in columns 3 and 7 which implies that the mean is higher than the median which is consistent with the right skewed distribution of estimated elasticities.

A second interesting result is that, when looking within firms percentiles, there are important gender

[2] This number is calculated using $w_m = \frac{p\frac{\partial Q(E_m,E_f)}{\partial E_m}}{\left(1+\frac{1}{\varepsilon_m}\right)}$ and $w_f = \frac{p\frac{\partial Q(E_m,E_f)}{\partial E_f}}{\left(1+\frac{1}{\varepsilon_f}\right)}$ which are obtained after solving the firm's profit maximization problem.

differences in lower percentiles (0.19 for men and 0.00 for women for the 25^{th} percentile when all separations are used). A difference that becomes smaller as we move up in the distribution (0.50 for men and 0.43 for women for the 50^{th} percentile) and reverses in the upper part of the distribution (0.89 for men and 0.99 for women for the 75^{th} percentile). The same pattern is observable when only quits are used.

We also observe from **Table 1** that differences across firms in the elasticity gap are much bigger than differences within firms. For example, when all separations are used, the higher within elasticity gap difference appears in the 25^{th} percentile with 0.19 and 0.00 for men and women respectively (a difference of 0.19). This difference is much smaller than the 0.7 and the 0.99 obtained between 75^{th}-25^{th} percentile for men and women respectively. This same pattern is observed when quits are used instead of all separations.

4.3 Between and Within Firms Differences

We do a complementary analysis to further investigate between versus within firms differences in gender-specific elasticities. For this analysis we use a sample of firms which only includes individuals who work at firms where we were able to estimate both, a male and a female labor-supply elasticity. This sample has 6,107,800 employment spells, belonging to 3,169,239 unique individuals, who work at 6,985 separate firms. In the upper panel of column 1 in **Table 2** we calculate the difference among these gender-specific elasticities suggesting, in our prefered model (full model time varying), that, on average, male elasticities between firms are 0.1 higher than female elasticities. In the second panel of column 1 in **Table 2** we present within firms differences which is calculated by taking the difference between male and female elasticities for each firm and then taking the average of the differences across firms. Results of our prefered model (full model time varying) suggest that on average male elasticities is 0.09 higher than female elasticities within firms, which suggests that when all separations are used there are no major differences in the elasticity gap between and within firms. However, when voluntary separations are used (column 2 in **Table 2**), between firms differences are more than twice the magnitude of within firms differences (in our prefered model). In other words, when voluntary separations are used between firms differences in elasticities are more important than within firms differences in elasticities.

This is a relevant result as regulations targeted at firms might be able to help address the gender gap, however it seems that the gender wage gap is driven more by structural factors that generate gender sorting to firms. This result is in line with Card et al. (2016) and Cruz and Rau (2017) for Portugal and Chile respectively whom, using a different approach, find that most of the wage gap is explained by sorting and a smaller part by bargaining power within firms.

5 Conclusions

The gender wage gap has been studied for decades, but usually from the perfect competition approach (Becker 1971). Models of imperfect competition (i.e., dynamic monopsony models) have only been recently applied to this topic. Moreover, due to data constraints, only recently empirical studies have attempted to analyze the gender wage gap using dynamic monopsony models; although most of these perform a market level analysis. An exception to this is Weber (2016), who estimates labor supply elasticities at the firm level for the US.. Due to data constraints, this study uses separations without identifying the source of separation. We contribute to the literature by being the first study that estimates labor supply elasticities using voluntary separations (i.e., quits). In particular, we estimate labor supply elasticities at the firm level for Chile (as Weber 2016 does for the US.) but also by identifying the source of separation (i.e. using voluntary separations). We find that using all separations increases the labor supply elasticities at the firm level by 18% relative to those found when voluntary separations are used. Thus, we find that using separations without identifying its source might bias results upward, suggesting that labor markets are more competitive than what they really are. Furthermore, when voluntary separations are used we find that between firm differences in the gender-specific elasticities are more relevant than within firm differences suggesting a relevant role of gender sorting to firms.

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Appendix

Table 1

Estimated Firm-level Labor Supply Elasticities and their Distribution

	All Separations				Voluntary Separations			
Model	Mean	25^{th}	50^{th}	75^{th}	Mean	25^{th}	50^{th}	75^{th}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male Elasticities								
Earnings only	1.05	0.61	0.94	1.45	0.96	0.42	0.80	1.42
No education controls	0.58	0.26	0.52	0.86	0.52	0.13	0.43	0.91
Full model	0.53	0.20	0.47	0.82	0.48	0.07	0.39	0.85
Full model time varying	0.56	0.19	0.50	0.89	0.49	0.00	0.39	0.92
Female Elasticities								
Earnings only	1.03	0.52	1.00	1.55	0.97	0.32	0.97	1.55
No education controls	0.44	0.02	0.38	0.88	0.41	0.00	0.37	0.98
Full model	0.45	0.02	0.38	0.91	0.38	0.00	0.34	0.97
Full model time varying	0.45	0.00	0.43	0.99	0.38	0.00	0.37	1.09

Three separate regressions, corresponding to equations (4)–(6), were estimated separately by gender for each firm in the data that met 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 log earnings. Second row also includes: age; age-squared; tenure, tenure squared, region, type of contract, number of employees working at the firm and industry indicator variables. Third row includes all previous controls plus 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)).The first column reports the firm labor-supply elasticity calculated with separations (i.e. voluntary and involuntary separations) while the fifth reports the same but using voluntary separations only (i.e. quits).

Table 2

Differences in labor Supply Elasticities

(Between and within firms)

	All Separations	Voluntary Separations
	Mean	Mean
	(1)	(5)
Differences Between Firms		
Earnings only	0.02	-0.07
No education controls	0.14	0.09
Full model	0.08	0.06
Full model time varying	0.10	0.07
Differences Within Firms		
Earnings only	0.03	-0.04
No education controls	0.06	0.01
Full model	0.03	0.03
Full model time varying	0.09	0.03

Note: Between firms differences among men and woman are obtained using firms that only includes individuals who work at firms where we were able to estimate both a male and female labor-supply elasticity. 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 6,107,800 employment spells, belonging to 3,169,239 unique individuals, who work at 6,985 separate firms.

Online Appendix

Descriptive Statistics

	Male		Female	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Unit of Observation: Employment Spell	(1)	(2)	(3)	(4)
Age (Years)	35.2	11.6	34.6	10.5
High School	0.29	0.46	0.23	0.44
High School Diploma	0.57	0.49	0.61	0.49
Some College	0.05	0.23	0.05	0.22
College Degree+	0.08	0.27	0.10	0.29
Spell Duration	17.7	24.4	20.4	26.5
Log(wages)	2.97	0.60	2.67	0.56
Wages (UF)	23.6	16.2	17.4	13.5
Observations	4,467,641		2,398,995	

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.