The Effects of Firms' Pay Policies and Equal Pay Laws on the Gender Wage Gap in Chile

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This paper assesses the total contribution of firm effects to the gender wage gap using a rich dataset of matched employer-employee data from Chile. We estimate two-way fixed effects models that allow us to decompose the contribution of firms to the gender wage gap into two channels: bargaining power and sorting effect. We also assess the effects of an Equal Pay law on both channels. We find that women receive about 88% of the firm-specific premium earned by men and that firms' total contribution explains about 49% of the gender wage gap. Sorting effects account for 70 to 80% of the firms' contribution, and the remainder is due to bargaining power effects. The gender wage gap slightly increases after the law, and there is no effect on neither bargaining power nor sorting effects.

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I. Introduction

Gender wage gaps are present in virtually every country in the world with significant levels of heterogeneity (Altonji and Blank, 1999; Blau and Kahn, 2000; OECD, 2012) and Chile is not an exception. Chilean female workers earn between 18 to 23% less than male workers, which places the country in the 60th percentile of the gender wage gap distribution among OECD countries (Perticará and Bueno, 2009; OECD, 2015).

The economic literature has traditionally associated the wage gap with different hypotheses, such as employer-based discrimination against women, differences in accumulation

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of human capital by gender, and labor costs related to hiring women, among others (Altonji and Blank, 1999; Blau and Kahn, 2000). An alternative explanation is that the gender wage gap would are due, in part, to differences in bargaining power between men and women at a given firm. Due to this firm-specific pay policy, the U.S. and many countries in Europe have approved equal pay laws (equal pay for work of equal value) and equal access to job postings for male and female workers.

As pointed out by Card, Cardoso and Kline (2016), there are two strands of the literature supporting that firm-specific pay policies may be relevant for understanding the gender wage gap. The first strands study the differences in the shares of men and women employed at different firms (Blau, 1977; Petersen and Morgan, 1995), and in the rates that men and women move to high-wage jobs (Hospido, 2009; Del Bono and Vuri, 2011). The other strand, based on laboratory experimental evidence, focuses on the bargaining power of employers and the possibility that women negotiate lower salaries (Bowles, Babcock and McGinn, 2005; Rigdon, 2012). These studies identify two different channels through which gender disparities may arise: a "sorting" channel that occurs if women are less likely to be hired at high-paying firms, and a "bargaining channel" that appears if women get a lower share of the "surplus" or rents associated with their job.

In this paper we estimate a two high-dimensional fixed effect wage model using matched employer-employee data from the Chilean Unemployment Insurance (UI) sample that allows us the identification of workers and firms fixed effects. We follow closely Abowd, Kramarz and Margolis (1999) and Card, Cardoso and Kline (2016) and decompose the firm's contribution to the wage gap to identify sorting and bargaining power effects. We find that the gender pay gap is 25% and firms' payment policies explain about 49% of this gap. Sorting effects account for about 71-81% and bargaining power effects for 19-29%. Also, it is found that women increase their salaries by about 15% less on average than men when changing jobs. Thus, even though sorting effects appears to be more important in explaining the gender wage gap, bargaining power effects can be as much as 29% of the total contribution of firms to these gender disparities.

The advantage of using Chilean data is threefold. First, the Chilean case gives a unique opportunity to assess the effects of equal payment laws on bargaining power and sorting effects. While equal pay laws were passed in the 70s, or early 80's in many countries (when there were no matched employer-employee data) it was only in 2009 when Chile passed Law 20.348 that establishes equal remuneration for work of equal value, allowing women to file a complaint if they face salary discrimination.[1] Thus, the Chilean context gives a unique opportunity to understand how equal payment laws may affect the wage gap: through the sorting channel and the bargaining power channel. This has not been studied before due to the lack of data at the time equal pay laws were passed in other countries. Second, I have access to rich administrative data from the UI that allows me to construct a long panel data with a sample size of nearly 60 million observations that guarantees representativity and consistency of our estimates. Lastly, it provides the first estimates of bargaining power and sorting effect in the context of a developing country where the institutions of the labor market are quite different to those in the developed world.

To the best of our knowledge, this is the first paper implementing AKM models to study the effects of an equal payment law on the contribution of bargaining power and sorting effects on the gender pay gap. Thus, it is novel to the international literature and relevant, not only from the academic point of view but also to inform public policies aiming at reducing the gender wage gap. Also, in the context of a developing country, this is the first paper estimating the contribution of firms on the generation of the gender wage gap.

II. Literature review

Despite political efforts to reduce the gender pay gap, men earn more than women in virtually every country (Altonji and Blank, 1999). This gap can be explained by several factors. For example, the economic sector and how male and female distribute in different industries (Jarrell and Stanley, 2004). However, the gender pay gap has a significant unexplained part, and the literature has proposed some hypotheses. Altonji and Blank (1999) explain two factors that can produce and affect the difference in wages between different groups: discrimination and human capital accumulation. For Latin America, Abramo and Todaro (2002) analyzes other channels such as the costs associated with hiring women due to legal maternity protection.

The empirical literature has used a variety of data sets to study wage differentials between men and women. Several studies have concluded that supply, demand, and institutions contribute to the wage gap, although at different rates in each country and periods (Katz and Autor, 1999). However, most studies have focused on employees and their observable skills, paying less attention to the employer's characteristics due to the difficulty in access-

[1] For instance, the 1969 Equal pay legislation in Ontario, Canada Gunderson (1985), the UK Equal pay Act in 1970, Manning (1996).

ing matched employer-employee data. This poses identification issues in the estimation of wage models as some theoretical advances have shown that firms' heterogeneity generates wage gaps between workers with identical skills within the same economic sector Burdett and Mortensen (1998). Moreover, recent developments have found that there is a specific contribution of employers to the wage differentials between individuals with the same skills (Lentz and Mortensen, 2010; Card, Cardoso and Kline, 2016) among others.

In this vein, Card, Cardoso and Kline (2016) study the effect of bargaining power of women relative to men in the generation of the wage gap. Their hypothesis is that women would get a smaller share of the profits of firms than men, given the lower bargaining power they exhibit. This idea is supported by recent developments in the experimental literature on bargaining power of women in wage determination.[2] While many authors share the idea that women and men differ in their ability to negotiate on wages, little is known about the quantitative impact of these differences in the gender pay gap. To test this hypothesis, they develop a model of gender wage determination with two high-dimensional fixed effects for the worker and the firm using administrative data from Portugal. They follow the seminal work of Abowd, Kramarz and Margolis (1999) on the identification and estimation of two-way fixed effect models using matched employer-employee data that allows identification of workers and firms fixed effects. They implement an Oaxaca-style decomposition to identify the firm contribution to the gender gap due to sorting, i.e. the effect due to female workers sorting into low-paying firms, and bargaining power effects, i.e. the effect due to the worker's ability to extract firm's rents when negotiating. They find that firm-specific contribution to the gender wage gap in Portugal is 20%, mainly driven by sorting effects. However, bargaining power effects explain about a fifth of the total contribution of firms to the gender wage gap.

In Chile, Ñopo (2007) analyzes the evolution of the gender wage gap from 1992 to 2003 using the decomposition technique developed in Ñopo (2004, 2008). He finds that "besides the high educational attainment of females", the gender wage gap is on average 25% (favoring males) and show no clear trend in the analyzed period. Interestingly, the decomposition technique identifies a "glass-ceiling effect", such that for some combinations of observable characteristics and occupations, there are highly paid males but not females. On the other hand, Perticará and Bueno (2009) find that, although there are still wage differences between

[2] Rigdon (2012) and Bowles et al. (2005) conducted laboratory experiments to observe the bargaining power of women in wage determination. The results are that women ask for less starting salary, which means they earn less than men. Also, women are less likely to initiate negotiations and are less effective in negotiating than men. The literature suggests that this may occur because women may feel less deserving of a monetary prize or because they expect a backlash if they negotiate for a right that belongs to them.

men and women, the introduction of controls of effective labor experience and the endogeneity of experience and education is corrected, the gender wage gap can be up to 18% (which is lower than previous studies, but still sizable and significant). Moreover, contrary to expectations, this gap has widened in the last years.[3]

III. Institutional background and data

In Chile, the female labor force participation rate is about 48% (INE, 2016), which is low relative to OECD and Latin American countries. However, in recent decades women have had a high incorporation into the labor market. Henríquez and Riquelme (2010) show that female labor force participation increased from 30.9 % in the 90's to 41.3 % in 2009; and the percentage of women contributing to household income rose from 28.7 % to 38.6 %. In addition, a third of Chilean households are headed by a woman and this proportion grows to 43.2 % in poor households and 47.9 % in the homeless, where often this is the only household income.

Although public policies targeted at increasing female labor force participation rate have had positive results, there are considerations that must be taken into account. For example, the incorporation has not been homogeneous; there is gender segregation in industries (Henríquez and Riquelme, 2010). Often this has meant that women are in lower quality jobs than men. Supplemental Income Survey of 2011 indicates that in sectors with high female concentration there is a significant fraction of precarious work with low productivity and poorly paid.

As mentioned before, recent measures of the gender wage gap indicates that Chilean female workers earn between 18 to 23% less than male workers, which places the country in the 60th percentile of the gender wage gap distribution among OECD countries (Perticará and Bueno, 2009; OECD, 2015). Although, this percentage is below than that of the 60s, when women got half the average wage earned by men, it is still sizable and significant (PNUD, 2010).

Aiming at reducing the documented wage gap, in 2009 an Equal Payment Law (Law 20,348) was enacted, being the most important regulation that has been passed on this subject in decades. This law requires firms with 10 or more permanent workers to establish a grievance procedure for any employee who feels discriminated against because of their gender.

[3] Other papers analyzing the gender wage gap in Chile are Bravo, Sanhueza and Urzúa (2008), Castaño and Paredes (2015), and Montenegro (2001) among others.

If a worker, who has followed the internal procedure defined in her company, has received no response or this has been unsatisfactory, she can denounce this in the Labor Inspection Office, which shall oversee the complaint. The participation of the Labor Inspection Office is not essential, since the worker may go directly to the labor courts.

Equal Pay laws focus on increasing bargaining power of female workers and reducing the gender bias (equal pay for work of equal value). Thus, to identify the success of this type of regulations is necessary to disentangle changes in the gender wage gap due to this channel (bargaining power) and other channels, such as sorting. Next section explains in detail how to achieve that.

The case of Chile is interesting to analyze for many reasons. First, even though gender wage gap exists in countries from a wide range of per capita income, it is more pronounced in developing countries. Second, there is a rich data set of matched employer-employee with monthly frequency and a generous time span (96 months). Third, an equal payment law was passed in the period analyzed that allows us to determine if equal payment laws affect, not only the wage gap, but also the bargaining power and sorting effect.

A. Data

The main source of information corresponds to a 30% sample of the population match employer-employee data from the Unemployment Insurance registry. By law, the Unemployment Fund Administrator is required to collect, on a monthly bases, all contributions to the unemployment individual accounts (and solidarity fund) for each labor relation. Hence, our data consider only formal workers that account for 80% of the labor force. The time span covered goes from October 2005 to October 2013. Specifically, we have access to individual characteristics such as age, education, gender, marital status, region, time of affiliation to the insurance, and monthly taxable income. Also, we have some information about employers: number of employees, industry, and region.[4]

With these data, we construct a monthly panel with all the relevant information for each individual. In Table 1 we present some descriptive statistics. Columns (1) and (2) show information for males and females in the overall sample and the rest of the columns to subsamples that are used to estimation of the double fixed effect models that will be

[4] The registry also includes information about application for withdrawals, such as the number of withdrawals an individual is allowed to collect, date and reason of application, date and reason of contract termination, former employer, S.U.F eligibility and SUF option. lastly, there is also information about withdrawals: data on each withdrawal amount and funding and data on suspended withdrawals.

discussed latter. We focus on males between 19 and 65 years and females between 19 and 60 years of age (female retirement age is 60 and male's retirement age is 65) with at least one year of effective experience in the formal labor market (more than 12 contributions). In the 2005-2013 period we have data for 1.1 million workers who are observed between 13 and 96 times (55 on average) with wage and employer identifier in each month. Since we have a monthly panel with relatively large span (96) we have many individual-month observations with more than 43 millions observations for males and almost 20 millions for women. Other features of the date are that females are younger, more educated, and earn 0.22 log points (24 %) less than males.

IV. Modeling framework

This section follows closely Card, Heining and Kline (2013) and Card, Cardoso and Kline (2016). This model presents the wages for workers in multiple periods. The model allows to observe the worker i working in the period t in the firm $j = j(i,t)$. Also, we observe the gender of the worker by $g \in \{F, M\}$.

Like a wage model, the worker earns a salary w_{ijt} in each period that is equal to the outside option (a_{it}) available to worker i and firm j in period t plus a gender-specific share ($\gamma^g \in [0,1]$) of the surplus (S_{ijt}) generated by the job match between worker i and firm j in period t.

$$w_{ijt} = a_{it} + \gamma^g S_{ijt}. \tag{1}$$

The literature argues that $\gamma^F < \gamma^M$, meaning that women obtain a lower proportion of the surplus of firms than their men colleagues. This is a key issue to test with data. The surplus S_{ijt} has three components:

$$S_{ij(i,t)t} = \bar{S}_{j(i,t)} + \phi_{j(i,t)t} + m_{ij(i,t)}. \tag{2}$$

The first component $\bar{S}_{j(i,t)}$, represents time-invariant factors. The second component, $\phi_{j(i,t)t}$, captures time-varying factors that change the surplus for the employees. The final term, $m_{ij(i,t)}$, is an individual worker component of surplus attending his particular abilities or characteristics.

The outside option for the worker, (a_{it}) is composed by three elements. First, permanent characteristics of each employee a_i (factors invariant in time). Second, a set of observable characteristics ($X'_{it}\beta^g$). Finally, a transitory component ε_{it}.

$$a_{it} = \alpha_i + X'_{it}\beta^g + \varepsilon_{it}. \tag{3}$$

These equations take to the following wage model:

$$w_{ijt} = \alpha_i + \psi^g_{j(i,t)} + X'_{it}\beta^g + r_{ijt}, \tag{4}$$

where $\psi^g_{j(i,t)} \equiv \gamma^g \bar{S}_{j(i,t)}$ and $r_{it} \equiv \gamma^g(\phi_{j(i,t)t} + c) + \epsilon_{it}$ is a composite error. This model has two way fixed effect estimation: workers and firms. This allows to analyze the difference between firm effect female and firm effect male.

A. Exogeneity

For unbiased estimates, the model has to comply the following condition

$$E\left[(r_{it} - \bar{r}_i)\left(D^j_{it} - \bar{D}^j_i\right)|G(i)\right] = 0 \ \forall j \in \{1, ..., J\} \tag{5}$$

where $D^j_{it} \equiv \mathbb{1}[J(i,t) = 1]$ indicates whether individual i is employed at firm j at time t and bars over D and r represents time averages. Card, Cardoso and Kline (2016) discuss three channels through which this condition would be violated and propose some graphical tests to assess the plausibility of the orthogonality condition. First, there should be neither an "Ashenfelter dip" in wages of job leavers prior to their exit, nor a wage growth for recent joiners. This will rule out connections between firm-wide shocks and mobility rates.The second channel refers to relation between mobility and idiosyncratic match effects between worker i and firm j. The mobility will be independent of the match effect if wage changes between workers who move move up and down is symmetric. The last channel relates to transitory wage shocks, for example, performance of worker in the firm before moving to another firm with higher or lower wages. That is, if a worker has good performance and get promotions in his firm is more likely to move to a higher wages firm, and the opposite.

B. *Normalization*

As noted by Abowd, Creecy and Kramarz (2002) and Card, Cardoso and Kline (2016) the two-way fixed effects (equation 1) are identified within a "connected set" of firms that are linked by worker mobility. Since there are more than one connected set, we estimate the models in the largest connected set, separately for men and for women. As in any fixed effect model, the fixed effects are relative to a base category (which is typically introduced as a linear restriction). Hence, the wage premium for any firm will be relative to a base category o reference firm.

Other feature of the estimated fixed effects in our unrestricted linear models is that there will be positive and negative firm fixed effects. However, in the model presented firm effects are non-negative. For this reason, a normalization was done for a set of "low-surplus" firms to 0.

In the normalization a "control industry" was used, one in which surplus captured by workers is 0. According to our data the fast food industry is close to this situation, in Card, Cardoso and Kline (2016) the hotel and restaurant sector was used to this end (in one of the specifications). It seems reasonable to assume that there is a very small wage premium on average, if any, due to low education, abilities and specialization in this kind of job.

C. *Sorting and Bargaining Effects at Firm-Level: Pay Premiums*

Using a sample of workers of firms that are doubly connected for males and females it is possible to decompose the difference between average pay premium received by each gender into bargaining power and sorting effects, in an Oaxaca-type wage decomposition. Note that the average pay premium received by males can be denoted as $E[\psi^M_{j(i,t)}|male]$ and the average premium received by females, similarly, as $E[\psi^F_{j(i,t)}|female]$. Taking the difference and doing a simple algebraic manipulation we can obtain the following decompositions:

$$
\begin{aligned}
(6)\qquad E[\psi^M_{j(i,t)}|male] - E[\psi^F_{j(i,t)}|female] &= E[\psi^M_{j(i,t)} - \psi^F_{j(i,t)}|male] \\
&+ E[\psi^F_{j(i,t)}|male] - E[\psi^F_{j(i,t)}|female] \\
(7)\qquad &= E[\psi^M_{j(i,t)} - \psi^F_{j(i,t)}|female] \\
&+ E[\psi^M_{j(i,t)}|male] - E[\psi^M_{j(i,t)}|female].
\end{aligned}
$$

The first term of the right hand side of equation (6) corresponds to the bargaining power effect, which can be obtained by taking the difference between ψ_j^M and ψ_j^F across the distribution of jobs held by male workers. The last term of the right hand side of equation (6) is the average sorting effect that compare the average value of ψ_j^F across the jobs held by male versus female workers. The equation (7) is an alternative decomposition, the bargaining power effect is estimated using the distribution of jobs held by female workers (first term), and the sorting effect is calculated by comparing the average value of the male pay premiums across jobs held by male versus female workers (second term).

V. Graphical evidence of firm-specific pay premiums

This section presents descriptive evidence to analyze and test some facts that are consistent with equation (4) and the exogenous mobility condition (5).

First, the sample described in columns 1 and 2 of Table 1 constructed mean log-worker wages for each person in each year and assign each person in each year the mean co-worker wages, independent of gender. With the mean co-worker wages, we created four quartiles per firm/year. We then selected workers who leave a firm after a minimum stay of two years, and moved to a new firm in which also stayed at least two years. We compute average wages in the years before and after the move for 16 groups by gender[5].

Figure 1 plots the wage trajectory for men before and after moving from the lowest quartile (1st) and for those who leave firms of the highest quartile (4th). Figure 2 shows the same but for women.

Table 2 summarizes all 16 possible movements (1st to 1st, 1st to 2nd, 1st to 3rd, etc.) groups of males and females. It also shows the number of cases and the average wage for each one.

With this descriptive evidence, we may analyze and test basic facts that are consistent with equation (4) and the exogenous mobility condition (5). First, workers who move between firms experiment changes in their salary. This suggest that there are significant firm-specific pay premiums component in the salary, valid for both gender.

Second, there are no wage shocks within the origin firm, for movers going to higher or lower wage, for example, from 4th to 1st or from 4th to 4th (the graphic shows parallel lines).

Third, Table 2 shows that wage changes for job changers who stay in the same quartile are all relatively small (an average regression-adjusted wage change for job changers using the

[5] 1st group: workers that leave firm of 1st quartile and join to firm of 1st quartile. 2nd group: workers that leave firm of 1st quartile and join to firm of 2nd quartile. Etc.

coefficients from a model of wage changes fit to the sample of job stayers who remain on the same job over a given four-year interval don't show significant difference). The average adjusted - e.g., 3% for female movers from quartile 1 jobs to other quartile 1 jobs, -1.4% for male movers from quartile 2 jobs to other quartile 2 jobs, and 0% for male and female movers from quartile 4 jobs to other quartile 3 jobs. This suggest that mobility per se has little effect on wage growth.

Fourth, the mean wage changes for workers who move in opposite directions between quartile groups are similar in magnitude. This is showed in Figure 3 and 4, which plot the mean adjusted wage changes for downward movers (e.g. form quartile 2 to quartile 1 firms) against the adjusted wage changes for symmetric upward movers (e.g. form quartile 1 to quartile 2). Almost all points are very close to a line with slope -1, this is consistent with the symmetry implications of an AKM model with exogenous mobility.

Finally, Figure 5 plots the adjusted wage change for each of 16 groups of the origin-destination quartiles for women against men. This shows that women gain less than men when changing to a better job and lose less when moving in the opposite direction. The slope in Figure 5 (0,86) could be seen as a difference in bargaining power of men and woman.

VI. Results

A. Estimation sample

We estimate equation 4 separately for men and women, including individual effect, firm effect, and individual characteristics such as age, schooling

The estimation sample corresponds to the largest connected set described in columns 3 and 4 of Table 1. As can be observed, and due to our long panel (96 months), the largest connected is about 95% of the overall sample. Thus, the generous length of the panel and the high level of labor mobility in the Chilean labor market allow to connect most of the firms in the period analyzed. Indeed, 95% of all person-month observations for male workers and 96% of all person-month observation for female workers are included in the largest connected set. More importantly, the characteristics of included workers in the largest connected set and those from the overall sample are very similar with the exception of the wage gap.

Once the AKM models are estimated for male and female workers, as in Card, Cardoso and Kline (2016) we focus on a narrow sample of workers of firms that are doubly connected: for men and women. In this set of firms, we are able to estimate exactly the same firm effects for both genders since the dual connections, which necessary to perform the Oaxaca-type wage decompositions. The dual-connected sample is described in columns 5 and 6 of table 1 and include about 90% of the observations in the overall analysis sample. As can be observed, the samples are quite similar with the exception of the wage gap, which is slightly higher in the dual-connected sample relative to the overall analysis sample (0.25 vs. 0.22 log points).

B. *Estimation results of worker-firm models*

In Table 3 we present the estimation results of the two fixed-effect model for men and women in the largest connected set of workers of each gender (described in columns 3 and 4 of Table 1).[6] The covariates included are workers and firm fixed effects, year dummies in level and interacted with four education categories (no education, primary, secondary and tertiary), plus quadratic and cubic age terms interacted with the education dummies.[7] We present some summary of parameter estimates such as the standard deviation of the person and firm effects, and the standard deviation of the the covariates (across person-month observations). As can be seen, person fixed effects and covariates have larger variances than firm effects. We present also the correlation of person and firm effects. For male workers the correlation is positive which means that firms that pay higher to workers tend to concentrate more highly skilled men. However the correlation for female workers is very small and negative. Evidence on the type of assortative matching is mixed. While positive assortative matching has been reported by Card, Cardoso and Kline (2016) in Portugal and Maré and Hyslop (2007) in New Zealand, negative assortative matching has been found in Washington state and France by Abowd, Kramarz and Pérez-Duarte (2003). Now, when calculating the correlation of male and female person effects the estimate is 0.79 suggesting that firms that pay higher to male workers do so for female workers as well.

We perform a decomposition of the variance of (log) wage across workers to examine the relative importance of the firm effects, measured as share of the variance. Te decomposition

[6] We use the Ouazad (2008) implementation of two way fixed effect model estimation due to the large amount of fixed effects in both levels: workers and firms. As pointed out by McCaffrey et al. (2012), this implementation is the fastest among all implementations reviewed by them and can be used with very large data sets, not requiring vast amounts of memory.

[7] As in Card, Cardoso and Kline (2016) we exclude a year dummy which in our case is 2005. The linear term in age is excluded as well to avoid collinearity between year and age when person effects are included. The age variable is re-centered at age 40 to avoid big numbers.

is simply

$$
\begin{aligned}
(8) \qquad Var(w_{it}) &= Var(\hat{\alpha}_i) + Var\left(\Psi^{G(i)}_{J(i,t)}\right) + 2Cov\left(\hat{\alpha}_i, \Psi^{G(i)}_{J(i,t)}\right) + Var\left(X'_{it}\hat{\beta}^{G(i)}\right) \\
&+ 2Cov\left(\hat{\alpha}_i + \Psi^{G(i)}_{J(i,t)}, X'_{it}\hat{\beta}^{G(i)}\right) + Var\left(\hat{r}_{it}\right).
\end{aligned}
$$

The variance decomposition across person-month observations in Table 3 show that the firm effects are sizable and explain about 19% and 14% of the log wage variance for men and women respectively. Individual characteristics and person effects explain other 50% and 54% for men and women as well. Lastly, residual variance accounts for 31% and 33%, which agrees with the R-squared of the models.

Lastly, Figures 6 and 7 show residual plots for models of male and female workers respectively. The figures plot mean residuals from estimated models in Table 3 for 100 cells, classified by decile of worker fixed effects and by decile of firm fixed effects. As can be seen, the residuals are negligible for both genders in all cells. The average residuals in absolute value are less than 0.03 which suggests that the log-linear specification of equation (4) provides a good approximation of the wage-determination process.

C. *The effect of firms on wage and its contribution to the gender wage gap*

Before presenting the results on firm-specific pay premiums and the gender wage gap, we need to normalize the firm effects since in the model the firm effects for each gender are non-negative, as explained in section IV.B. Then we need to identify the threshold level of the surplus paid by firms, such that firms with surplus below that threshold are considered "no surplus firms". We use firms in the fast food industry as the "no surplus" ones since we observe that fast food firms have one of the smallest wage premium on average in our data. With this normalization about 18.9% of the person-month observations have a "no surplus" firm effect.[8]

As we discuss later, the normalization of the firm effects does not affect the estimation of the sorting effects (those are invariant to normalizations) but they do affect the bargaining effect. In the appendix we present an alternative normalization using firms in the hotel industry as a robustness check, finding similar results.

[8]In one of the specification implemented by Card, Cardoso and Kline (2016) they use hotel and restaurants as no surplus firms for normalization of the firms effects finding similar results to their normalization based on value added. In the latter, they obtain a 9% of the person-year observations in "no surplus" firms in their data.

Now, we quantify the effect of firm-specific pay premiums using the normalized firm effects for male and female workers. In Table 4 we present the results for different subsamples. The first row show the results for the entire dual connected set. Column (1) shows that the wage gap in this sample is 0.25 log points. Columns (2) and (3) show the male and female premia and column (4) the difference between the two, which corresponds to the total contribution of firms to the wage gap. Thus, about 49% of the wage gap (0.12 log points) is explained by firms. In the case of Portugal, this share varies between 21 and 29% depending on the normalization. Now in columns (5) to (8) we compute the four terms contained in equations 6 and 7. When the Oaxaca-type decomposition in equation 6 is implemented we have that nearly 0.09 log points (out of the 0.12) are explained by sorting effects (column 5). This corresponds to almost 35 percentage points (pp), out of 49, of the total contribution of firm components. The rest, 0.036 log points, are explained by sorting effects (column 8) that corresponds to 14 pp of the total contribution of firm components. On the other hand, when equation 7 is implemented, the sorting effect increases to 0.10 log points (about 39 pp) and the bargaining power effect decreases to 0.02 log points (about 9 pp). As in the case Portugal, the sorting effect is the leading term in the decomposition, however, the bargaining power effect is sizable and contributes to the wage gap between 0.023 and 0.036 log points.

Compared to the evidence presented by Card, Cardoso and Kline (2016), the total contribution of firm effects are higher in Chile (49%) than in Portugal (20-29%). However, the importance of the sorting effects over the bargaining power effect is similar in both countries. Depending on the Oaxaca decomposition implemented (equations 6 or 7), in Portugal the sorting component is between 70 and 95% of the total firm contribution to the wage gap and in Chile between 71 and 81%. The differences in total contribution may be due to differences in the institutions of the labor market, the strength of equal pay regulations[9], cultural factors, among other reasons. We rule out the firm effects normalization in explaining this total contribution difference. As explained before, the sorting effect is not altered by the normalization and in both countries it is the most important firm component contributing the wage gap. If we believe that the share of the sorting effect is similar in both countries, we can recover the total contribution in a straightforward manner and check that total contribution of firms component in Chile is close to that reported in Table 4.[10]

[9]As in other european countries, the idea of equal pay for work of equal value has been stated in the Portuguese national constitution and can be found also in different Parliament Acts.

[10]For instance, using the decomposition form equation 6, the sorting effect is 0.087 log points and is not affected by the normalization. If this is the 70% of the total contribution, as in Portugal, the total contribution of the firm effect is 0.087/0.7=0.124 which is very close to the 0.122 computed contribution.

We also implement the decomposition in different subpopulations. In particular we explore the heterogeneity of the effects by age (up to age 30, between 31 and 40, and over age 40) and education (less than high school, high school and some college and more) group and by type of contract (permanent or fixed term contract). As can be observed, the gender wage gap increases with age, is relatively stable by education group and is higher for those with fixed term contract relative to workers with permanent contracts. Interestingly, the total contribution of firm components in the gender wage gap decreases monotonically with age and decreases (non monotonically) with education. Sorting effects are the most important component of the total contribution of firm component. However, for more educated workers (university) the bargaining power effect explains considerably more of the firms contribution to the wage gap than that of those with high school or less education (see columns 7 and 8 for the three education groups).

D. Sorting, Bargaining, and the Equal Pay Law

In order to assess the effects of the Equal Pay Law on bargaining and sorting effects, we propose an augmented version of equation (4) given by

$$w_{ijt} = \alpha_i + \psi^g_{j(i,t)} + \chi^g_{j(i,t)} \times Post_t + X'_{it}\beta^g + r_{ijt}, \tag{9}$$

where $Post_t$ is a dummy variable equal to one when t is after the Equal Pay Law and zero otherwise. The terms $\chi^g_{j(i,t)}$ correspond to the changes in firms fixed-effects after the law. Then, $\psi^g_{j(i,t)}$ are the firm fixed-effects before the law and $\psi^g_{j(i,t)} + \chi^g_{j(i,t)}$ those after the law. With these fixed-effects we are able to implement decompositions (6) and (7) and evaluate how the bargaining and the sorting effects change after the reform.

Identification of the firm fixed-effects in equation (9) requires a connected set among firms before and after the reform. Implementation of decompositions (6) and (7) requires also dual-connected sets (connected sets for men and women) among firms before and after the reform. Thus, we are able to estimate the same firm effects for both genders, before and after the reform.

Now, estimating equation (9) implies increasing the dimensionality of the firm fixed-effects which intensify the computer burden. We implement decompositions (6) and (7) in a simpler way.

As discussed in section III, in november 2009 an Equal Payment law entered into force in Chile. Hence, we split the sample into two subintervals spanning the period from 2005 to 2013 to implement a before and after the enactment of the equal payment law comparisons to assess its effects on the wage gap, the total contribution of firm effect components to it and its decomposition into sorting and bargaining power effect. This allows to changes in the firm fixed-effects but also in all parameters (individual fixed-effects and covariates).

In Table 5 we present the results for these two periods. In panel A, we can see the results for the "before the law" period and in Panel B for the after the law period. As observed, when considering the entire sample (first row in panels A and B) the wage gap increases after the law and the total contribution of firm effects remains about the same in the two periods (45.6 pp before vs 44.9 pp after the law). When analyzing the decomposition of the total contribution of firms effects into the wage gap, the evidence favors the hypothesis that the law did not affect neither the bargaining power effect nor the sorting effect.

VII. Conclusions

We study the firm-specific determinants of the gender wage gap using using a rich dataset of matched employer-employee data from Chile. We estimate two-way fixed effects models and implement recent methodologies that allows us to decompose the contribution of firms to the gender wage gap into two channels: bargaining power and sorting effect.

The main results indicate that women receive about 88% of the firm-specific premium earned by men and that firms' total contribution explains about 49% of the gender wage gap. Sorting effects accounts for 70 to 80% of the firm effect, which gives a small room to equal pay laws to alter the gender wage gap, typically aimed at affecting the bargaining power channel.

We estimate the models before and after the enactment of the equal payment law to assess if this type of initiatives are able to affect the bargaining power or the sorting channel determining the gender wage gap. We find an increase in the gender wage gap and no effect on any of the two analyzed channels.

Table 1—: Descriptive Statistics for three different samples

			Connected Sets of Workers/Firms			
	Overall analysis		All-Connected		Dual-Connected	
	Males	Females	Males	Females	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)
Age:						
Mean Age	38.6	37.3	39.0	37.3	39.0	37.2
Fraction $\leq$ 30 years old	0.26	0.30	0.27	0.30	0.27	0.30
Fraction $\geq$ 50 years old	0.21	0.14	0.20	0.14	0.20	0.14
Education:						
Mean Years Schooling	9.4	10.0	9.2	9.5	9.2	9.5
Fraction with High School	0.51	0.57	0.51	0.57	0.51	0.57
Fraction with Degree	0.08	0.12	0.08	0.12	0.08	0.12
Mean Log Real Wage	8.09	7.87	8.11	7.87	8.12	7.87
(standar dev.)	(0.83)	(0.82)	(0.83)	(0.82)	(0.83)	(0.82)
Fraction in Metropolitan Region	0.55	0.56	0.56	0.57	0.56	0.57
Mean Firm Size (No. emp's)	8	11	8	13	10	10
Fraction Females at Firm	0.52	0.28	0.22	0.68	0.44	0.44
Number person-month obs.	43,399,448	19,968,097	40,934,561	19,838,918	38,905,314	19,363,458
Number of persons	745,123	404,486	706,686	388,109	701,751	386,798
Number of firms	227,376	159,434	138,325	120,436	107,509	107,509

Notes: Overall analysis sample (columns 1 and 2) includes male formal workers between 19-65 years and female formal workers between 19-60 years (retirement age for female is 60 and male is 65). COMPLETAR

Table 2—: Wages of Job changes for Movers with 2+ Years Data Before/After Job Change

Origin/ destination quartile	Number Changes (1)	Pct. of Changes (2)	Mean Log Real Wages of Movers: 2 years before (3)	1 year before (4)	1 year after (5)	2 years after (6)	3 Year Change (%) Raw (7)	Adjusted (8)	(Std Err) (9)
Males									
1 to 1	5,968	25.0	7.56	7.48	7.57	7.66	9.9	-4.0	(1.2)
1 to 2	6,892	28.9	7.68	7.58	7.78	7.87	19.1	5.2	(1.2)
1 to 3	5,900	24.7	7.67	7.51	7.92	8.04	37.8	23.9	(1.2)
1 to 4	5,080	21.3	7.76	7.63	8.25	8.44	67.9	53.5	(1.3)
2 to 1	5,132	13.8	7.75	7.66	7.61	7.73	-1.3	-12.2	(1.0)
2 to 2	10,792	29.0	7.79	7.72	7.80	7.89	9.7	-1.4	(0.9)
2 to 3	11,288	30.3	7.86	7.78	7.98	8.11	25.0	13.4	(0.9)
2 to 4	10,064	37.0	7.94	7.83	8.30	8.43	53.8	41.4	(0.9)
3 to 1	3,568	6.3	7.97	7.85	7.63	7.77	-19.3	-31.8	(0.7)
3 to 2	9,528	16.7	7.97	7.88	7.82	7.94	-2.2	-14.5	(0.7)
3 to 3	21,148	37.1	8.09	8.02	8.09	8.21	12.5	0.0	(0.7)
3 to 4	22,792	40.0	8.20	8.20	8.41	8.56	36.2	-22.3	(0.6)
4 to 1	1,756	2.2	8.29	8.20	7.76	7.95	-33.7	-53.3	(0.5)
4 to 2	4,520	5.7	8.32	8.20	7.97	8.12	-19.2	-39.1	(0.5)
4 to 3	12,584	15.8	8.42	8.34	8.25	8.40	-1.9	-21.3	(0.5)
4 to 4	60,844	76.3	8.77	8.72	8.83	8.97	20.2	1.0	(0.4)
Females									
1 to 1	7,792	37.5	7.26	7.25	7.37	7.43	17.4	3.0	(1.0)
1 to 2	7,368	35.4	7.38	7.34	7.56	7.64	25.6	11.2	(1.0)
1 to 3	3,512	16.9	7.48	7.35	7.76	7.89	41.3	26.8	(1.2)
1 to 4	2,124	10.2	7.59	7.41	8.10	8.27	67.7	52.5	(1.4)
2 to 1	3,716	18.4	7.59	7.52	7.49	7.60	0.8	-10.3	(0.8)
2 to 2	6,844	33.9	7.65	7.59	7.68	7.79	13.9	2.2	(0.8)
2 to 3	5,464	27.0	7.75	7.67	7.87	8.00	24.6	12.1	(0.8)
2 to 4	4,176	20.7	7.85	7.75	8.19	8.35	49.6	25.8	(0.9)
3 to 1	1,764	8.1	7.78	7.67	7.50	7.65	-13.1	-26.5	(0.6)
3 to 2	4,284	19.7	7.81	7.73	7.72	7.87	5.9	-8.3	(0.6)
3 to 3	8,492	39.0	7.98	7.93	8.01	8.12	14.2	0.0	(0.6)
3 to 4	7,248	33.3	8.14	8.07	8.32	8.48	33.2	17.6	(0.7)
4 to 1	840	3.0	8.20	8.11	7.87	8.02	-18.4	-38.4	(0.4)
4 to 2	1,480	5.3	8.24	8.13	7.93	8.11	-13.2	-34.5	(0.4)
4 to 3	4,800	17.3	8.36	8.31	8.22	8.37	1.1	-20.0	(0.4)
4 to 4	20,632	74.3	8.72	8.67	8.76	8.89	17.3	-3.1	(0.4)

Notes: columns 4 to 6 present mean log real wages for wages at the old job and the destination new job. Origin/destination quartiles are based on mean wages of coworkers in year before (origin) or year after (destination) job move.

Table 3—: Summary of Estimated Two-way Fixed Effects Models for Male and Female Workers

	All Males (1)	All Females (2)
Standard deviation of log wages	0.827	0.821
Number of person-month observations	40,934,561	19,838,918
Summary of Parameter Estimates:		
Number of person effects	706,686	388,109
Number of firm effects	138,325	120,436
Std. dev. of person effects (across person-month obs.)	1.835	1.359
Std. dev. of firm effects (across person-month obs.)	0.361	0.304
Std. dev. of Xb (across person-month obs.)	1.721	1.337
Correlation of person/firm effects	0.071	-0.011
RMSE of model	0.462	0.471
Adjusted R-squared of model	0.682	0.664
Correlation of estimated male/female firm effects	0.79	
Variance decomposition of two-way fixed effects model:		
Share of variance of log wages due to:		
firm effects	19.0	13.7
person effects, Xb and covariances	49.8	53.5
residual	31.2	32.8

Notes: See text. Models includes dummies for individual workers and individual firms, year dummies interacted with education dummies, and quadratic and cubic terms in age interacted with education dummies (total of 40 parameters). Samples include only observations in largest connected set.

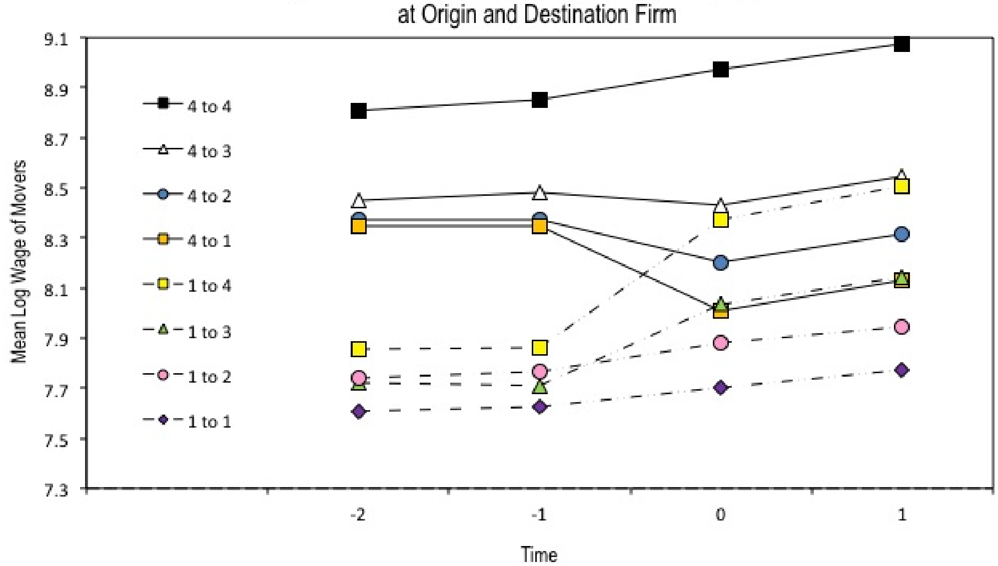
Table 4—: Contribution of Firm-Specific Pay Premiums to the Gender Wage Gap at Dual Connected Firms

		Means of Firm Premium:		Total	Decompositions of Contribution of Firm Component:			
					Sorting		Bargaining	
	Gender Wage Gap	Male Premium Among Men	Female Premium Among Women	Contribution of Firm Components	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All	0.251	0.331	0.209	0.122	0.087	0.099	0.023	0.036
				(48.7)	(34.5)	(39.3)	(9.3)	(14.2)
By Age Group:								
Up to Age 30	0.145	0.293	0.193	0.100	0.067	0.080	0.020	0.033
				(69.0)	(46.1)	(54.9)	(14.1)	(22.8)
Age 31-40	0.193	0.353	0.235	0.118	0.079	0.089	0.030	0.040
				(61.5)	(40.8)	(46.0)	(15.4)	(20.7)
Over Age 40	0.352	0.333	0.193	0.140	0.107	0.120	0.020	0.033
				(39.7)	(30.3)	(33.9)	(5.8)	(9.4)
By Education Group:								
Less than High School	0.311	0.300	0.165	0.135	0.102	0.122	0.012	0.032
				(43.3)	(32.9)	(39.3)	(4.0)	(10.4)
High School	0.290	0.345	0.209	0.136	0.100	0.107	0.029	0.036
				(46.9)	(34.3)	(36.7)	(10.1)	(12.6)
University	0.328	0.449	0.324	0.126	0.081	0.070	0.055	0.045
				(38.3)	(24.6)	(21.5)	(16.8)	(13.7)
Type of Contract:								
Permanent	0.253	0.373	0.248	0.125	0.081	0.084	0.041	0.044
				(49.5)	(32.0)	(33.1)	(16.4)	(17.5)
Fixed Term	0.343	0.280	0.145	0.135	0.113	0.133	0.002	0.022
				(39.3)	(32.9)	(38.8)	(0.5)	(6.4)

Table 5—: Contribution of Firm-Specific Pay Premiums to the Gender Wage Gap before and after of Equal Pay Law

		Means of Firm Premium:		Total	Decompositions of Contribution of Firm Component:			
					Sorting		Bargaining	
	Gender Wage Gap	Male Premium Among Men	Female Premium Among Women	Contribution of Firm Components	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Before Equal Pay Law (2005-2009)								
All	0.245	0.295	0.183	0.112	0.071	0.094	0.017	0.040
				(45.6)	(29.2)	(38.6)	(7.0)	(16.4)
By Age Group:								
Up to Age 30	0.124	0.248	0.163	0.085	0.049	0.072	0.013	0.036
				(69.0)	(40.0)	(58.1)	(10.8)	(29.0)
Age 31-40	0.163	0.310	0.205	0.105	0.059	0.079	0.025	0.045
				(64.2)	(36.4)	(48.7)	(15.5)	(27.8)
Over Age 40	0.352	0.303	0.173	0.130	0.092	0.117	0.013	0.037
				(36.8)	(26.2)	(33.2)	(3.5)	(10.6)
By Education Gruop:								
<High School	0.311	0.269	0.146	0.123	0.088	0.119	0.004	0.035
				(39.3)	(28.2)	(38.2)	(1.2)	(11.1)
High School	0.275	0.307	0.185	0.122	0.081	0.098	0.025	0.042
				(44.5)	(29.3)	(35.4)	(9.0)	(15.1)
University	0.321	0.397	0.280	0.117	0.064	0.062	0.055	0.053
				(36.4)	(19.9)	(19.2)	(17.2)	(16.5)
Type of Contract:								
Permanent	0.233	0.332	0.218	0.114	0.062	0.074	0.040	0.052
				(48.9)	(26.8)	(31.6)	(17.2)	(22.1)
Fixed Term	0.344	0.254	0.133	0.121	0.098	0.129	-0.008	0.024
				(35.2)	(28.4)	(37.6)	(-2.4)	(6.9)
Panel B: After Equal Pay Law (2009-2013)								
All	0.280	0.319	0.193	0.126	0.092	0.103	0.023	0.033
				(44.9)	(33.0)	(36.9)	(8.1)	(11.9)
By Age Group:								
Up to Age 30	0.166	0.287	0.186	0.101	0.070	0.080	0.019	0.031
				(61.0)	(42.4)	(49.5)	(11.5)	(18.6)
Age 31-40	0.242	0.344	0.215	0.129	0.090	0.097	0.031	0.039
				(53.2)	(37.2)	(40.3)	(12.9)	(16.0)
Over Age 40	0.386	0.320	0.178	0.142	0.112	0.124	0.018	0.030
				(36.9)	(29.0)	(32.1)	(4.7)	(7.8)
By Education Gruop:								
< High School	0.335	0.293	0.158	0.134	0.108	0.125	0.010	0.026
				(40.2)	(32.3)	(37.2)	(2.9)	(7.9)
High School	0.318	0.330	0.193	0.137	0.1031	0.108	0.029	0.034
				(43.0)	(32.3)	(34.1)	(9.0)	(10.7)
University	0.337	0.416	0.285	0.131	0.078	0.072	0.059	0.053
				(39.0)	(23.2)	(21.4)	(17.5)	(15.7)
Type of Contract:								
Permanent	0.286	0.352	0.222	0.130	0.085	0.089	0.041	0.045
				(45.3)	(29.6)	(31.1)	(14.3)	(15.7)
Fixed Term	0.366	0.276	0.143	0.133	0.120	0.134	-0.001	0.013
				(36.2)	(32.7)	(36.6)	(-0.4)	(3.6)

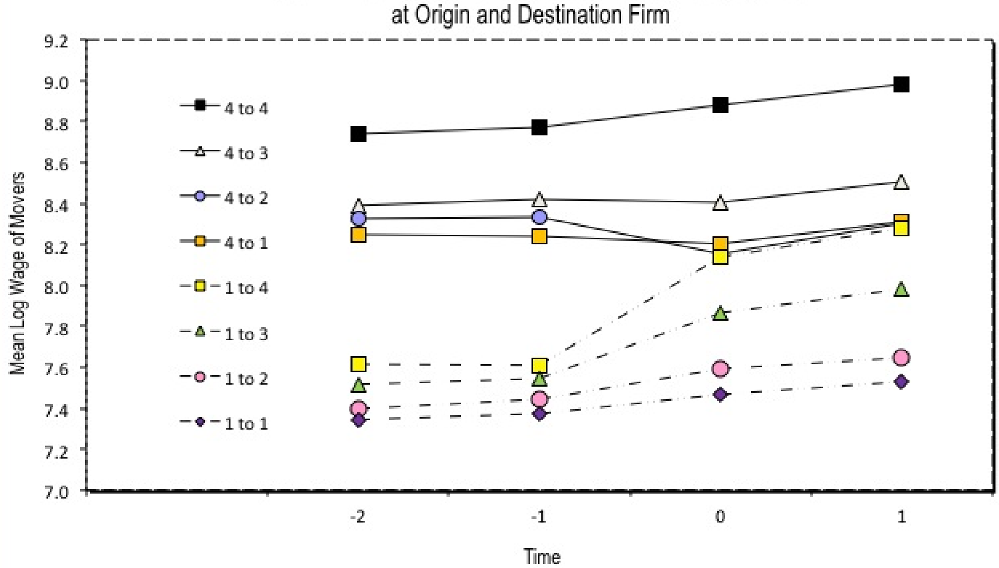
Figure 1: Mean Wages of Male Job Changers by Quartile at Origin and Destination Firm



Notes: (1) Figure shows mean wages of female workers at mixed gender firms who changed jobs and who were at least 2 years on old job and 2 years on new job. Each job is classified into quartiles based on mean log wage of co-workers.

(2) -1 = last year on old job; 0 = first year on new job.

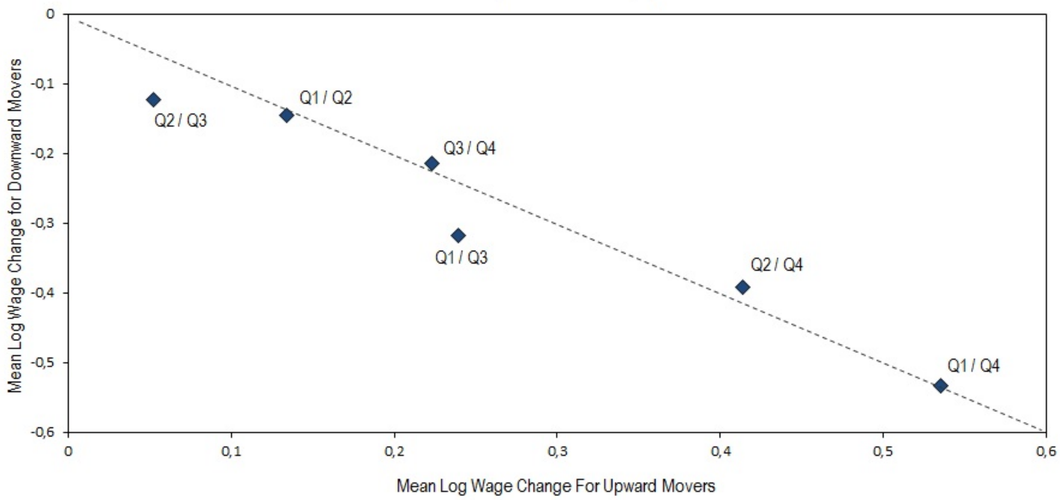
Figure 2: Mean Wages of Female Job Changers by Quartile at Origin and Destination Firm



Notes: (1) Figure shows mean wages of female workers at mixed gender firms who changed jobs and who were at least 2 years on old job and 2 years on new job. Each job is classified into quartiles based on mean log wage of co-workers.

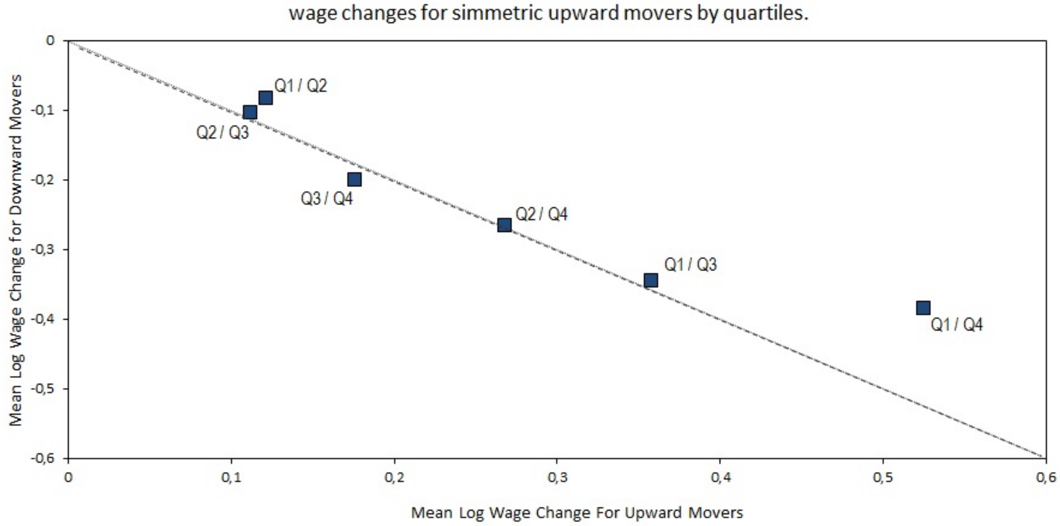
(2) -1 = last year on old job; 0 = first year on new job.

Figure 3: Mean adjusted Male wage changes for downward movers against the adjusted wage changes for simmetric upward movers by quartiles.



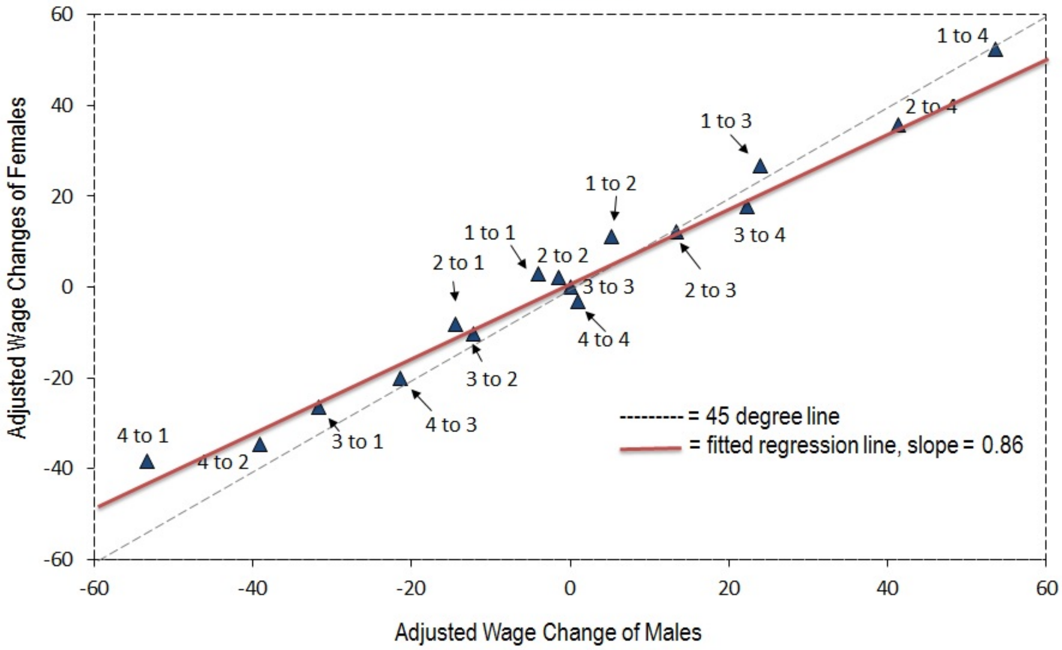
Note: (1) Figure graphs the mean adjusted wage changes for downward movers (eg, from quartile 1 to quartile 2, versus from quartile 2 to quartile 1).
(2) Dashed line represents symmetric changes for upward and downward movers.

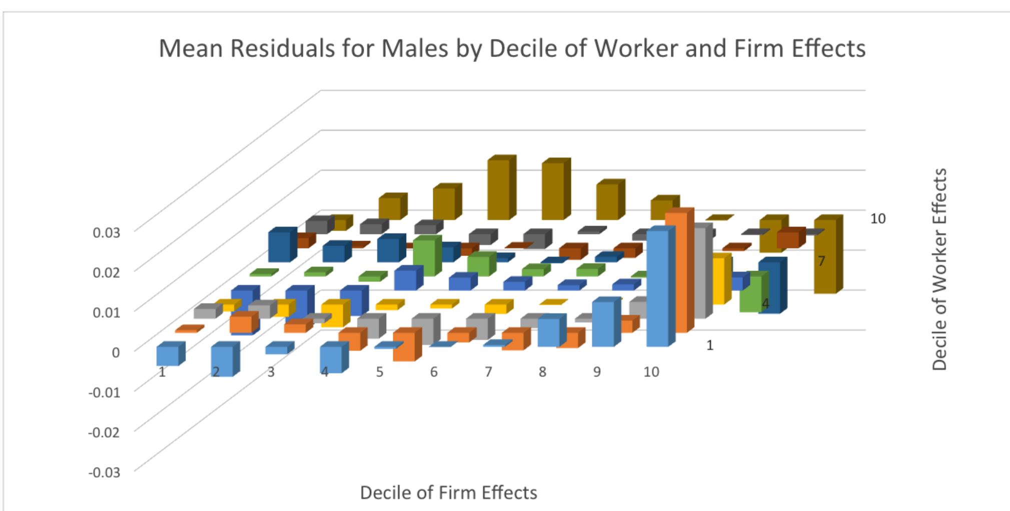
Figure 4: Mean adjusted Female wage changes for downward movers against the adjusted wage changes for simmetric upward movers by quartiles.

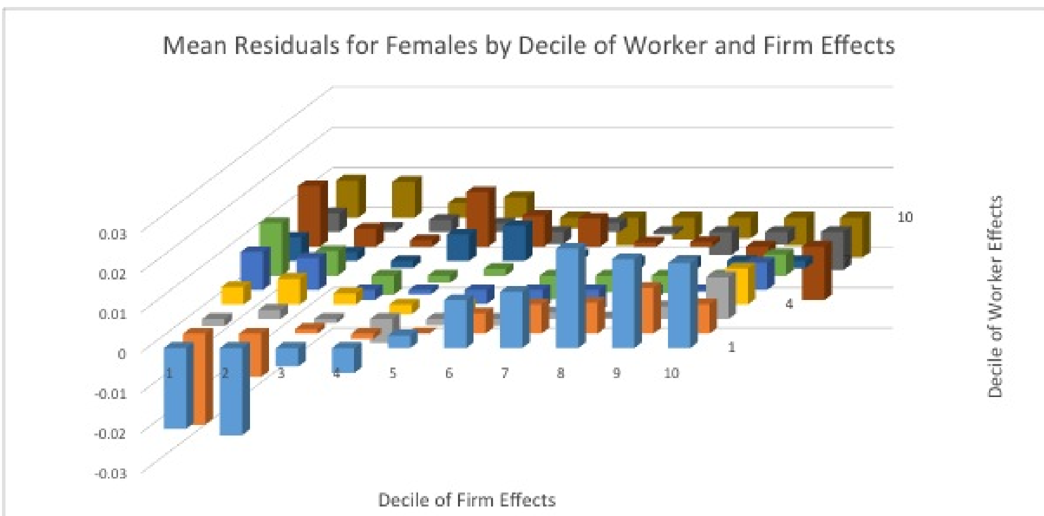


Note: (1) Figure graphs the mean adjusted wage changes for downward movers (eg, from quartile 1 to quartile 2, versus from quartile 2 to quartile 1).
(2) Dashed line represents symmetric changes for upward and downward movers.

Figure 5: Difference of Adjusted Wage Changes between Male and Female by Quartile of Origin and Destination Jobs.







Mean Residuals for Females by Decile of Worker and Firm Effects
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
1
2
3
4
5
6
7
8
9
10
1
4
10
Decile of Firm Effects
Decile of Worker Effects

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