POSTGRADO ECONOMÍA Y NEGOCIOS
UNIVERSIDAD DE CHILE

“Firm-specific Pay Policies Importance on the Gender Wage Gap after Equal Pay Law”

TESIS PARA OPTAR AL GRADO DE

MAGÍSTER EN ECONOMÍA

Alumno: Beatrice Allamand Turner

Profesor Guía: Esteban Puentes Encina

Santiago, noviembre 2021

Firm-specific Pay Policies Importance on the Gender Wage Gap after Equal Pay Law *

Beatrice Allamand Turner †

November 25, 2021

Abstract

This paper analyses Chile's narrowing Gender Wage Gap in light of the Equal Pay for Equal Work Law (EPL) promotion in 2009. We use matched employer-employee data to estimate two-way worker-firm fixed-effect models, decomposing the firm's contribution to the pay gap into bargaining and sorting channels and its evolution in the 2010-2020 period. While our data show a reduction in the gap over time, we find that the firms' contribution increases steadily. Firm-specific pay policies explained a 22% of the gap in 2010-2013, while they end up explaining a 53% in 2016-2019. Growth in the bargaining channel mainly drives this evolution, while sorting decreases its importance over time. In addition to past studies, these results suggest that while firms may have restructured their salary schemes because of EPL, they managed to accommodate and keep their gender-differentiated pay premiums. We do not have evidence to relate the fall in the gap to the wage policies firms implemented, if not despite them.

1 Introduction

Since the Equal Pay for Equal Work Law (EPL) promotion in 2009, Chile's Gender Wage Gap remained constant until 2016 and witnessed a drop to date. This fact may prove the importance of promoting equal wage regulations. Alternatively, the falling gap can be the result of other factors, such as the growing female entry to the labor market, the increasing participation of women in male-dominated areas, the increase in female enrollment in the universities, the greater participation of women in senior positions or company boards, etc. While this progress might still be due to the regulation indirectly, we are interested in assessing the importance of EPL on reducing gender-differentiated firm-based pay policies. We will not directly study EPL implementation, but we will examine the evolution of the firm contribution to the gender wage gap, looking for evidence of how we expect the law to have affected. To that end, we study

*Powered@NLHPC: This research was partially supported by the supercomputing infrastructure of the NLHPC (ECM-02).
†mallamand@fen.uchile.cl

the evolution over time of the firm's specific pay component of the gender wage gap, from 2010 to 2020, by estimating an Abowd, Kramarz, and Magnolis (1999) [AKM from now on] wage model for men and women in sample partitions. This model provides estimators of firm-specific pay premiums for each worker from which we can compute the gender gap on wage premiums and its contribution to the gender wage gap. Furthermore, we study the evolution over time of the channels explaining the firm's contribution to the gap. Those are the Bargaining channel and Sorting channel.

In a world of perfect competition in the labor market, wages are determined by workers' productivity. On the other hand, if firms exhibit some level of market power, they can pay salaries below each worker' productivity. This markdown depends on how elastic each worker's labor supply is. If, in addition, we have deviations from perfect competition in the final product markets, firms will have different productivity premiums, and therefore, rents to be distributed to workers will also differ between firms. We decompose the contribution of the firms to the gender wage gap between bargaining and sorting channel based on these two theoretical observations. When employed in the same firms as men, women could have lower salaries if their work supply is steeper by receiving wages that exhibit larger markdowns below their productivity (Bargaining channel). Also, they could end matched with lower productivity firms, which have fewer rents to distribute to both men and women (Sorting channel). If policies of "equal work, equal pay" at the firm level explained the narrowing of the gender wage gap, we should expect a decrease in the bargaining channel, as firms should start paying equal markdowns disregarding the difference between men and women's labor supply. An equal pay law should not directly affect the sorting channel, but the cultural change it may carry can indirectly affect the matching between firms and female and male workers.

We find that, while the gender wage gap decreases over the period, the gap between the firm-specific pay premiums that men and women receive becomes larger and larger. These two facts explain that the gap that the firms represent rises from 22% to 53%, growing consistently in each sub-sample and each specification we estimate.

The bargaining channel explains this sustained increase regarding the channels that make up the firm's contribution to the gap, growing from between -0.02 and -0.04 of a difference in 0.09 on premiums (22% of the gap) up to between 0.05 and 0.03 of a difference of 0.10 (53% of the gap). While the differences between male and female premiums across female or male jobs (bargaining) grow across the period, the difference in the average compensation of men and women across their job distribution decreases (sorting) from between 0.09 and 0.07, to between 0.07 and 0.06 showing that women's capacity for positive sorting improves over time, but the more significant worsen of their bargaining conditions make the firms component of the gap to increase across the period.

Our results suggest that the drop in the wage gap observed in the period is not due to the correction in the firm's wage policies after EPL. Nevertheless, we see that EPL might be improving the positive sorting capacity for women as an indirect effect.

This paper builds upon the results of Cruz and Rau (2017), who showed that EPL reduced the firm pay premium gap by 6.1%, which was entirely driven by the bargaining power channel. The effects they found were more significant in firms exposed to higher penalties and disclosure requirements. While these findings may sound conflicting with our own, they are accordant, as our estimations on the equivalent subsamples are similar. The aggregation of both results suggests that firms first reacted to EPL restructuring their wage schemes, reducing their gender-based differentiated pay policies. But then, Firms accommodated the regulation and found new ways of passing different premiums on male and female workers.

If it were cost-efficient for firms to have gender-differentiated salary schemes prior to the law, and the fines are small, it may be cost efficient for companies to return to or even have maintained those schemes and pay the penalties. Alternatively -and independently if we consider the fines small or not-, motivated by reducing costs, firms may aim to keep their wage schemes avoiding the penalty. The law establishes that equal work must be paid equally, but firms can find ways to redefine their workers' functions to explain different wages. Firms will try to keep their wage schemes either by paying the fine (if it is profitable) or looking for ways to avoid its payment. Both tracks are compatible with the fact that women saw their bargaining power improve relative to men in the first years after the law, but then it worsened, returning to previous levels.

Finally, if we believe the fines are low, it is possible that the firm wages' restructuration was influenced to a greater extent by the political, social, and media impact of the new law than by the economic incentives the law entailed. It is reasonable to think that this influence is temporary, while the restructuration would be more permanent if significant economic incentives were behind it.

Although we can build this bridge between the two articles, our paper does not pretend to study the effect of the law directly. Instead, motivated by (1) the marginal drop in the gap from 2009 to now, (2) the severe concerns that the community has had about the ineffectiveness of the law, and (3) the few complaints filed [1], we want to understand the evolution of the wage gap and the importance of firm-based pay policies in its determination from 2010 to date. We seek to answer whether women receive lower, higher, or equal

[1] According to administrative data, in September 2020, there where 12 processes identified as causes of remuneration discrimination between women and men, in which, based on a difference in remuneration for the same job, the purpose of the process is to determine whether it configures violation of the norm. In addition, only in 5 of these cases, the respective court has accepted the action (Rojas, 2021 [**?**]).

firm-specific premiums relative to men today than 10 years ago. We want to know how the above has evolved. Has it consistently improved or worsened over time since EPL? We find that, even though the wage gap rises and remains stable between 2010 and 2016, and falls between 2016-2020, the importance of market power increases steadily in the 2010-2020 period. In other words, if the gap has decreased over time, it is not thanks to the wage policies that companies implement, but despite them. The reasons for the drop in the gap in our model are the accumulation of education, experience, and skill (captured by the fixed worker effect) of women relative to men. It is not clear, and it is not the purpuse of this article to identify EPL's impact. Still, if there had been an essential effect in the medium and long term, we would have found that the negotiation channel explaining the gap did not increase over time. However, we find it increases. On the other hand, the association channel -which measures how much of the gap is explained by the fact that female workers pair with less productive companies relative to similarly productive men- falls over time, showing that the sorting ability of women improves, maybe as a result of EPL.

2 Firm-specific Determinants of the Gender Wage Gap

2.1 Labor Market Power

In recent years, studies that seek to explain wage dispersion from the perspective of the importance of the firm have proliferated. Models have different microfoundations, as market power can be defined by (1) frictions in search [Postel-Vinay and Robin (2002), Taber and Vejlin (2018)], (2) market concentration [Berger et al. (2019), Jarosch (2019)], (3) differentiated works or taste for amenities [Sorkin et al. (2018), Card et al. (2018), Lamadon et. al (2019)]. However, they agree that firms face a positive slope labor supply, with elasticities different than infinity. Thus, contrary to the prediction of perfect competition, the firm is relevant - not just the market - when determining wages. They also agree that the equilibrium wage will be a mark-down below the marginal productivity of workers. According to each base model, this mark-down will depend on the job supply elasticity faced by the firm, taste for amenities parameters, the index used to measure the concentration of the market, etc.

The most traditional way of studying the impact of market power on wages is to measure how much income shocks in firms are transmitted to wages. These studies are known as rent-sharing literature. If permanent productivity increases are not transmitted 1:1 to workers' wages, imperfect competition exists. Rent-sharing literature finds wage to value-added elasticities between 0.05 and 0.15. Meaning the pass-through of a 1% value-added shock is only 0.10%.

On the other hand, Firm effects literature estimates the effect of market power on wage dispersion by measuring what part of the variance of wages is explained by the variance in firm-specific premiums. It builds from the two-way fixed effects wage model proposed by AKM. Using data from worker-firm matches, AKM estimates firm-specific and worker-specific pay premiums. Most studies find that the variance of wages attributed to the firms' effects is around 20%, meaning market power explains 20% of wage inequality.

Recent literature (Bonhomme et al. (2019), Lamadon et al. (2019), and Kline et al. (2018)) on labor market power has posed some challenges regarding the use of AKM models to estimate the role of firms and market power in determining wage inequality. Lamadon et al. (2019) show that the results of Card (2018) overestimate the firm effect and underestimate sorting. Furthermore, this work suggests that firm effects are neither implied nor do they imply rents. To measure the importance of market power, they state that one must estimate wages' sensitivity to changes in productivity.

2.2 Gender Wage Gap

Until recently, Gender wage gap literature mainly considered wage dispersion from differences between markets: differences in human capital, schooling, return on human capital, compensatory differentials, etc. Even discrimination literature is at the market level, as the preference of the marginal employer in a market determines discrimination.

For the same reasons one expects that the firm's identity will be relevant in determining workers' wages and the income distribution, one should expect there will be effects of the firm and market power in the gender wage gap.

A significant amount of the literature that studies the gender gap builds from the importance of the firm. It is the case of the models that explain the wage gap from differences between men and women in willingness to and success in negotiating their wages (Rigdon (2012), Bowles (2007)) and the case of Supply-based Models. Models that build from differences in bargaining power do not explicitly refer to the fact that there is market power in the labor market since they are natural experiments. Still, market power must be a characteristic of the underlying labor market. Otherwise, the bargaining capacity of workers would not be relevant in determining wages at the firm level. Models based on labor supply are explicit in modeling market power since, for example, they explain the wage gap from the different elasticity of the supply of men and women (As do Caldwell (2018), Bhalotra (2018), Gosh (2018)). Some venture to model the demand for labor of firms with CES production functions that consider women and men as substitute / complementary factors, which they define by estimating the elasticity of substitution, with changes in female labor supply and how they affect employment (this is the case of Bhalotra (2018) and Gosh (2018)).

Sanchez (2019) estimates male and female labor elasticities for Chile, finding that different labor supply elasticities between men and women may account for the whole wage gap in our country.

2.3 Gender Wage Gap and Labor Market Power

Card et al. (2016) or CCK, is the first paper that directly incorporates market power into studying the wage gap. This work has been widely replicated. It is the case of Bruns (2019) for West Germany (2001-2008), Coudin et al. (2018) for France (1995-2015), Casarico y Lattazio (2019) for Italy (1995-2015), Sorkin (2017) for the US (2000-2008) and Cruz and Rau (2017) for Chile from 2006 to 2013. CCK propose estimating two AKM salary models, one for men and the other for women, from where they recover estimators of the firm fixed effects. Then, they can evaluate the difference in firm premium between men and women. In addition, they perform a comparison exercise to estimate rent-sharing, thereby confirming their results in light of the challenges faced by the AKM literature. Our study closely follows the CCK methodology too.

2.4 Our Study

As stated earlier, we want to understand the evolution of the wage gap and the importance of firm-based pay policies in its determination from 2010 to date. We seek to answer whether women receive lower, higher, or equal firm-specific premiums relative to men today than 10 years ago. We want to know how the above has evolved since EPL.

The novelty of our study concerning the literature that studies the relationship between firm-specific bonuses and the wage gap, is that it is the first to estimate gender-differentiated AKM models in successive time windows, to obtain estimators of the evolution in the time of firm effects (which are generally assumed to be fixed in time). Contrary to that assumption, we expect that the salary bonuses that men and women receive due to market power may change over time.

Almost every study cited earlier was built using annual data [Card et al., 2016; Bruns, 2019; Coudin et al., 2018; Casarico y Lattazio, 2019; Sorkin, 2017]. For this type of study, the panel will have eight periods if they have an eight-year panel. It is impossible to estimate fixed effects in short term windows for these panels for two reasons: (1) each sub-panel of two or three years would have to have just two or three period observations, and even more importantly (2) the low labor mobility present in the developed economies studied by these countries (Portugal, France, USA, etc.) makes the Connected Set an even smaller sample in these sub-samples.

Our data allows us to build a panel whose observation unit is a monthly worker-firm match. We have, for a 10-year window, 120 periods. Therefore, it is possible to separate the sample and estimate in successive windows of 2 or 3 years, leaving each with 24 and 36 periods, respectively.

Labor mobility in Chile is very high compared to the countries where these studies have been carried out. Measured as the rate of entry / exit to new jobs at the firm level, it is 37% for the period 2005-2014 (Albagli et al., 2017), which is well above the 20% estimated for a sample of 25 OECD countries (Bassanini and Garnero, 2013). This characteristic of the Chilean employment dynamics allows that even in short time windows, workers connected through movements between companies constitute an important portion of the sample[2].

Cruz and Rau (2017) divide their sample into 2: November 2005 - November 2009 and December 2010 - November 2013. They use the companies of the original connected set that are in both periods. They estimated 31,933 company fixed effect observations in each period (well below the 108,235 companies present in its Dual-Connected Set [19 million obs., 398 thousand people]). Our entire period has 29 million observations in the Dual-Connected Set, 643 thousand workers, and 125 thousand companies. In each estimation of 3-years sub-periods, we have between 7 and 8 million observations, approximately 400 thousand workers and 48 thousand companies, then 48 thousand observations of fixed firm effects per period. Although Cruz and Rau use our same monthly observation unit, our data allows a greater disaggregation into periods. The reason for this has to do with the origin and evolution of the unemployment insurance database[3].

Therefore, the novelty of being able to estimate the AKM model in sub-periods of 2 and 3 years is possible thanks to (1) the panel unit is monthly, (2) between 2010 and 2020 most of the formal contracts have already been renewed since 2002 and therefore are at the base of unemployment insurance and (3) the high mobility of workers between jobs in Chile. These characteristics allows us to estimate not 1 fixed-effects

[2]For the two-year sub-samples, the connected sets for men they constitute between 86 and 90%, and for women between 85 and 80%. For the three-year sub-samples, the largest connected set of the men's sample contains between 93 and 90% of the workers, while for women it contains between 89 and 86%.

[3]The unemployment insurance law contemplates all contracts signed since October 2002. Contracts are not renewed every year, so it took time for the database accounting for the unemployment affiliates to become representative of formal wage earners in Chile. During 2003, insurance affiliates increased from 800 in January to 2 million in December (from 15 to 40 % of the self-employed and salaried employees estimated based on the National Employment Survey of INE). Thus, for 2006 (the first year in the Cruz and Rau sample) the unemployment insurance data continues to leave many contracts (all those aged four or more years old) out. As of 2006, the insurance only contained 4 million affiliates, approximately 70 % of the estimate of employed and self-employed workers for that year (5.7 million). Members reach 100% of the contracts described in 2009. It is to be expected that as of 2010 there are still contracts that have not been renewed since 2002, however these are a smaller proportion. Using the same panel, but in later periods (2010-2020 vs 2006-2013), allows us wealthier data due to the greater proportion of information on formal workers available.

model but 3 (subsamples of 3 years) and even 5 (subsamples of 2 years). This way, we can deviate from the assumption that the wage premiums paid by companies to women and men are stable over time. Our study proves that they are not; instead, they have a particular dynamic that remains for future research to explain in depth.

3 Institutional Setting and Data Overview

3.1 EPL

EPL (Law No. 20,348), active since November 2009, establishes that employers must comply with the principle of equal pay between men and women who perform the same job. Specifically, it requires firms with ten or more permanent workers to establish a grievance procedure for any employee who feels discriminated against because of their gender. EPL also mandates firms with 200 or more workers to describe all positions in the company according to their essential technical skills (disclosure requirement). There are monetary penalties for firms that violate the law, varying by firm size as measured by the number of permanent workers by month. Firms with 10 to 49 workers face a fine of UTM 9 (CLP 481.284, nearly USD 600). Those with 50 to 199 workers face fines of UTM 30 (CLP 1.604.280, nearly USD 2000). Lastly, firms with 200 or more workers face fines of UTM 40 (CLP 2.139.040, approximately USD 2600). Although we do not pretend to evaluate EPL's effect directly, this penalty structure allows us to somehow see the law's impact by comparing the evolution of the gender wage gap at firms affected by the law (+10 workers) and those who were not (-10 workers). As Cruz and Rau (2017), we present the results of our decomposition by firm size to shed light on the above.

3.2 Data

We use 20% of the Unemployment Insurance affiliates to build a panel which's unit of observation is the monthly worker-firm match.

A separated AKM wage equation is estimated for females and males, for the whole period and for different partitions of the period to see the evolution of the estimators. The full sample goes from July 2010 to June 2020. The main sub-period specification estimates the model on 3-years samples that go from September to September every three years (September 2010 - September 2013, September 2013 - September 2016, September 2016 - September 2019). Each of this subsamples has 36 periods, as our data is on monthly worker-firm matches. Another specification is estimated with smaller windows of time (each sub-sample consists of 2 years of data, 24 periods) and includes 2019 (from October) and 2020. These 2-years samples go from July to June every two years (July 2010 - June 2012, July 2012 - June 2014, July 2014 - June 2016, July 2016 - June 2018 and July 2018 - June 2020).

Since the estimation of our wage equations uses heavy computing, models are run at Chile's National High Performance Computing Laboratory (NLHPC).

We have access to individual characteristics such as age, education, gender, and monthly taxable wages. For firms, we have industry information, the number of workers employed, mean wages paid, and region. We focus on workers between 19 and 60 years of age, as 60 is the age of retirement of women in Chile. For the 2010-2020 period we have data for 2 million workers, who are observed between 1 and 120 times with an employer identifier each month. As our time span is large, we have many individual-month observations with more than 54 million for men and 32 million for women. Because of our large span, we deflate wages with the monthly Consumer Price Index. Our data lacks hours worked, so some of our results may be confounding pay premiums with compensated differentials. To reduce this possibility, we only include observations where the wage is higher than the minimum wage. Some workers have more than one monthly contract because they work at more than one firm or even appear to have more than one contract in the same firm. When a worker appears more than once, he is matched with the firm that pays a higher wage. We construct a monthly panel described in Tables **??** to 6 for our different specifications with this data. Tables 3 and 5 present the count of monthly person observations, workers, and firms for the Males and Females models, at each sample of interest. Table **??** presents the full period and 2-years sub-periods specifications, and Table 5 the 3-years sub-periods specification. The full sample consists of the original sample after the minimum wage, unique job, and CPI adjustments. The largest connected set refers to the sample's most extensive set of connected firms through worker mobility. Finally, Dual connected set represents the firms and workers connected both in the female and the male specification. The analysis of firms' contribution to the gender wage gap is built upon the dual-connected sample. Tables 4 and 6 present some descriptive statistics for the three different samples. While Table 4 does this for full sample and two-period sub-samples identification, Table 6 does the same for the three-years specification.

4 Modeling Framework

In this section, we present the wage model used by CCK. We begin with a wage model that conceives that the match between a worker and a firm generates surplus (final product market power). Also, that firms pass this surplus to workers' wages on a fraction smaller than 1:1 (labor market power). The final equation is a two-way fixed effects model. We run a gender-differentiated AKM, meaning AKM wage equations on men and women separately. Its estimation provides us estimators on person effects, gender-specific firm effects, and gender-specific returns to covariates.

The logarithm of the real wage earned by individual i in period t, of gender $G(i) \in \{F, M\}$ employed at firm $J(i,t) \in \{1, \ldots, J\}$ is given by:

$$logw_{it} = a_{it} + \gamma^{G(i)} S_{iJ(i,t)t} \tag{1}$$

Where

- a_{it}: represents the outside option available to worker i on period t that can be decomposed into a permanent component α_i (due to ability or skills), a time-varying component associated with an observed set of characterstics X_{it} (labor market experience and changing returns to education), and a transitory component ε_{it}:

  $$a_{it} = \alpha_i + X_{it}' \beta^{G(i)} + \varepsilon_{it}$$

  Where $\beta^{G(i)}$ is a gender specific vector of coefficients.

- $S_{iJ(i,t)t}$: is the match surplus between worker i and firm $J(i,t)$ in period t. It can be decomposed into three components:

  $$S_{iJ(i,t)t} = \bar{S}_{J(i,t)} + \phi_{J(i,t)t} + m_{iJ(i,t)}$$

  - $\bar{S}_{J(i,t)}$: captures time-invariant factors like market power or brand recognition that raise the average surplus for all employees at a firm.
  - $\phi_{J(i,t)t}$: represents time-varying factors that raise or lower the average surplus for all employees.
  - $m_{iJ(i,t)}$: captures a personal specific component of surplus for worker i at his or her current employer, attributable to ideosyncratic skills or characteristics that are particularly valuable at this job.

- $\gamma^g \in [0, 1]$: gender-specific share of the surplus captured by a worker of gender $g \in \{F, M\}$.

Where g and j denote a gender and firm in particular. We believe labor market power implies wages represent a mark-down below workers' competitive wage that equals their productivity, so we think of a_{it} as a value below the competitive wage. Workers get paid a salary above or equal to a_{it}, but still below the competitive wage they should have earned if there were perfect competition on both labor and final product market. Therefore, we understand $\gamma^{G(i)} S_{iJ(i,t)t}$ as a gender-differentiated firm specific premia, that is additive and positive. This doesn't mean that workers' get larger wages when employed at firms that have higher rents, because even when rent-sharing is close to 1:1, they will still earn a mark-down below their productivity.

We are specially interested in the question of whether women get a smaller share of the surplus associated with their job, that is $\gamma^F < \gamma^M$.

Using the definitions provided, (1) can be written:

$$logw_{it} = \alpha_i + \varphi^{G(i)}_{J(i,t)} + X'_{it}\beta^{G(i)} + \epsilon_{it} \tag{2}$$

With

- $\varphi^{G(i)}_{J(i,t)} \ \equiv \ \gamma^{G(i)}[\bar{S}_{J(i,t)}]$
- $\epsilon_{it} \ \equiv \ \gamma^{G(i)}[\phi_{J(i,t)t} + m_{iJ(i,t)}] + \varepsilon_{it}$

As said at the beginning of this section, equation (2) is consistent with an additive two-way worker-firm effect model of the type AKM, with person effects, gender-specific firm effects, and gender-specific returns to covariates.

Identification of (2) requires a range condition that imposes a selection over the original sample as coefficients can only be estimated over a connected set of firms. Consequences of this selection will be covered on section 5.1. Unbiased identification of the coefficients requires that the assumption $E(\epsilon) = 0$ is plausible. Exogeneity is not realistic to presume as mobility is endogenous (workers choose when and where to move) but it is only necessary to prove that mobility behaves as if it were exogenous. More of this discussion is covered in section 4.1.

We can estimate AKM's typical variance decomposition separately for the female and male sample:

$$V(lnw_{it}) = \underbrace{V(\hat{\alpha}_i)}_{person\ effects} + \underbrace{V(\hat{\varphi}^{G(i)}_{J(i,t)})}_{firm\ effects} + \underbrace{2cov(\hat{\alpha}_i, \hat{\varphi}^{G(i)}_{J(i,t)})}_{sorting} + \underbrace{2cov(\hat{\alpha}_i + \hat{\varphi}^{G(i)}_{J(i,t)}, X'_{it}\hat{\beta}^{G(i)}) + V(X'_{it}\hat{\beta}^{G(i)})}_{X\beta\ and\ covariances} + V(\hat{\epsilon}_{it}) \tag{3}$$

Where firm effects (FE) will tipically refer to plug in estimators of the share of log wages variance explained by firm fixed effects variance.

$$FE = \hat{\theta}^g = \frac{V[\hat{\varphi}^g_j]}{V[lnw_{it}]}$$

4.1 Exogeneity

We estimate models based on equation (2) by OLS, yielding estimated gender specific effects for each firm. For these estimates to be unbiased, the following orthogonality conditions must hold:

$$E\Big[(\epsilon_{it} - \bar{\epsilon}_i)\big(D^j_{it} - \bar{D}^j_i\big)|G(i)\Big] = 0 \ \ \forall\ j \in \{1, \ldots, J\}, \tag{4}$$

where $D_{it} \equiv 1\ [J(i,t) = j]$ is an indicator for employment at firm j in period t and bars over variables represent time averages. With two periods, fixed effect estimation is equivalent to first differences estimation and (4) becomes:

$$E\Big[(\epsilon_{i2} - \epsilon_{i1})\big(D^j_{i2} - D^j_{i1}\big)|G(i)\Big] = 0 \ \ \forall\, j \in \{1, \ldots, J\}, \tag{5}$$

where

$$\big(D^j_{i2} - D^j_{i1}\big) = \begin{cases} +1 & \text{for workers who move to firm } j \text{ in period 2} \\ -1 & \text{for workers who leave firm } j \text{ in period 1} \\ 0 & \text{for others} \end{cases}$$

We can write (5):

$$E\Big[(\epsilon_{i2} - \epsilon_{i1})\big(D^j_{i2} - D^j_{i1}\big)|G(i)\Big] = E\Big[\epsilon_{i2} - \epsilon_{i1}\big|D^j_{i2} = 1, D^j_{i1} = 0, G(i)\Big] * Pr\big(D^j_{i2} = 1, D^j_{i1} = 0|G(i)\big) \tag{6a}$$

$$- E\Big[\epsilon_{i2} - \epsilon_{i1}\big|D^j_{i2} = 0, D^j_{i1} = 1, G(i)\Big] * Pr\big(D^j_{i2} = 0, D^j_{i1} = 1|G(i)\big). \tag{6b}$$

The term in (6a) is the mean change in the unobserved wage determinants for joiners of firm j multiplied by the probability that a worker of gender $G(i)$ joins firm j from time 1 to 2. The term (6b) is the change for leavers of this firm, multiplied by the probability that workers leave the firm between 1 and 2. Hypothetically, it is possible that these two terms are comparable in magnitude since the decision to leave a firm is a decision to join another. If that is the case, the bias associated with joiners and leavers would cancel if the number of joiners and leavers is the same (employment at the firm is in steady state). Nevertheless, (5) would be violated if the joiner and leaver bias -even when cancelled at the firm level- differs significantly across firms.

Since $\epsilon_{it} = \gamma^{G(i)}[\phi_{J(i,t)t} + m_{iJ(i,t)}] + \varepsilon_{it}$:

$$\epsilon_{i2} - \epsilon_{i1} = \gamma^{G(i)}[\phi_{J(i,2)2} - \phi_{J(i,1)1} + m_{iJ(i,2)} - m_{iJ(i,1)}] + \varepsilon_{i2} - \varepsilon_{i1},$$

three channels may generate bias through firm specific mobility: a connection between firm shocks $\phi_{J(i,t)t}$ and workers mobility $m_{iJ(i,t)}$, a relationship between mobility and idiosyncratic match effects and a correlation between mobility and the transitory wage shock ε_{it}.

We will be looking for evidence on these on our data, represented graphically in mobility figures from 8 to 25.

The first channel relates to the fact that workers may be more likely to leave firms experiencing adverse shocks and join firms experiencing positive shocks. This be the case, we would notice a decline in the wages of leavers prior to exit and an unusual wage growth for recent joiners. We generally found no evidence of these patters in our , but there is some evidence this be the case for women in lower paying firms (females who move from a firm in the first quartile, to a firm in the second quartile of income), in the last sub-period of the three-year sample estimation (2016-2019) as can be seen in figure 15, and on the last two periods of the two-years sample estimation (2016-2018, 2018-2020) as can be seen in figures 23 and 25.

The second channel provides bias if mobility is dependant of the match effects. It is actually the case that many search and matching models assume, because workers search over jobs that differ by a match effect in pay. An implication is that the wage gains of movers will overstate the gains of a typical worker and in the limit, all moves will lead to a wage gain. In our model, we see workers moving in opposite directions between groups of high and low wage firms.We show that their wage changes exhibit the approximate symmetry predicted by an additive model with exogenous mobility. This symmetry can be seen in figures from 8 to 25, for the different estimation samples.

Finally, the third channel arises if the direction of firm to firm mobility is correlated with the transitory wage shock. That is to say, a worker who is performing well and receiving promotions may be more likely to move to a higher wage firm, while workers stalled at their job may be more likely to move to a lower wage firm. If this trend is systematic, we will see that people moving to higher-wage firms will have different prior wage trends that those who move to lower-wage firms. Our analysis finds no evidence of these predictions, as we see across figures the evolution between periods 0 and 1 does not depend on the fact that the worker is moving to a higher or a lower quartile.

If (4) holds, OLS $\hat{\varphi}_j^g$ is unbiased but noisy. It's square will be biased upwards, which is what happens with point estimates of the classical AKM firm effect (contribution of firm fixed effects variance to total wage variance). This bias is known as the limited mobility bias. It biases the plug-in estimator of the firm effect upwards, and that of the sorting effect downwards. The magnitude of both biases is inversely dependent on worker's mobility.

4.2 Normalization

Since the wage premium for any given firm is only identified relative to a reference firm, we require a linear restriction to normalize the firm effects. According to our model, the true firm effects for each gender are non-negative and zero at firms that offer no surplus above an employee's outside option. We, therefore, normalize the firm effects by setting the average wage premium for a set of low-surplus firms to 0. As we lack information of value-added per firm, we normalize the firm effects by assuming that firms in the hotel and restaurant industry pay zero surplus on average, as do CCK do on one of their specifications[4]. This assumption is motivated by the extensive literature on industry wage differences which suggests rents drive these differentials. The normalized firm fixed effects are:

$$\tilde{\varphi}^g_{J(i,t)} = \varphi^g_{J(i,t)} - E(\varphi^g_{J(i,t)}|G(i) = g, I_{J(i,t)} = 1)\ ,\ g \in \{F, M\},$$

where $I_{J(i,t)}$ corresponds to the industry of firm $J(i,t)$ and takes the value of 1 when it is a part of the hotel and restaurant industry.

4.3 Decomposing the effect of firm level pay premiums

Two channels may explain the different pay premiums that men and women receive on average. The first channel is known as the bargaining channel, and it refers to the fact that women may be less willing to and less successful at negotiating their wages than men. If no bargaining occurs at the firm level, we can think of this channel as the difference between male and female premiums at the same firms. The second channel is sorting. It captures the difference in pay premiums between men and women attributable to the identity of firms male and female workers end up matched to. A female worker may be as productive as a male worker, but if employed at a firm that pays more extensive markdowns below productivity to all workers, she will have a lower wage.

The difference in the firm-specific premium that men and women earn on average can be decomposed between sorting and bargaining channels in two ways, as proposed by CCK. Using $male$ and fem as shorthands for the conditioning events that G(i)=M and G(i)=F, and expressing $\varphi^{G(i)}_{J(i,t)}$ as the normalized firm fixed effects, we can denote the average pay premium received by men as $E(\varphi^M_{J(i,t)}|male)$, and the average pay premium received by women as $E(\varphi^F_{J(i,t)}|fem)$. We have:

$$E(\varphi^M_{J(i,t)}|male) - E(\varphi^F_{J(i,t)}|fem) = \underbrace{E(\varphi^M_{J(i,t)} - \varphi^F_{J(i,t)}|male)}_{bargaining} + \underbrace{E(\varphi^F_{J(i,t)}|male) - E(\varphi^F_{J(i,t)}|fem)}_{sorting} \tag{7a}$$

$$= \underbrace{E(\varphi^M_{J(i,t)} - \varphi^F_{J(i,t)}|fem)}_{bargaining} + \underbrace{E(\varphi^M_{J(i,t)}|male) - E(\varphi^M_{J(i,t)}|fem)}_{sorting} \tag{7b}$$

- **Bargaining channel:** It is built comparing $\varphi^M_{J(i,t)}$ and $\varphi^F_{J(i,t)}$ across the distribution of jobs held by men (7a) or women (7b).

[4]CCK normalized the firm's fixed effects to those with zero surpluses based on value-added data in their main specification. The authors use hotels and restaurant firms as zero surplus firms in a robustness check specification, finding similar results. Cruz and Rau (2017) use food industry firms as no-surpluses firms in their preferred specification and hotel firms in their robustness check.

- **Sorting channel:** It is obtained comparing the average $\varphi^{F}_{J(i,t)}$ (7a) or $\varphi^{M}_{J(i,t)}$ (7b), for the male against the female jobs distribution.

5 Estimation of Worker-Firm Models

5.1 Estimation Sample

We estimate equation 2 separately for men and women, including individual effects, firm effects, and individual characteristics such as age and education.

The estimation sample corresponds to the largest connected set described at Tables 1 to 4. As can be observed, the largest connected set includes a 96% of male and 94% of female workers for the whole period specification. For the sub-period two-year specifications this set includes between the 86 and 90% of men, and the 80 and 85% of women. For the 3-year sub-periods analysis, this set accounts for between 90 and 93% of men, and 89 and 86% of women. More importantly, the mean characteristics of workers included in the largest connected set and those of workers from the overall sample are very similar, as can be seen in Tables 2 and 4.

Once the AKM models are estimated for male and female workers, as in CCK, we focus on a narrow sample of workers at firms that are doubly connected, that is, connected at the same time for men and women. In this dual-connected set, we estimate fixed effects for each firm for both genders to perform the Oaxaca-type wage decompositions presented at section 4.3. As can be seen in Table 3, the dual-connected set sample includes 90% of the male and 91% of the female workers at the full period specification. For the 2-year sub-periods the women in the dual connected set range between 74-79% of the full sample, and men range between 69-75%. Table 5 shows that for the 3-year sub-periods, women in the dual connected set range between 81-84%, and men between 90-93%.

Whether our findings can explain the evolution of Chile's gender wage gap in time depends on the departure of our data from the reality of most firms and workers in Chile. Table 7 compares the gap our original data (Full sample) presents, with the gap present in the estimation sample (connected sets; Largest CS) and the decomposition sample (dual connected set; Dual CS), across models. The dual connected set presents a larger gender wage gap than the largest connected set and the full sample. As can be seen in Table 4 for the full period and two year sub-periods and in Table 6 for the three year sub-periods, the need to connect the data imposes a selection to our sample of bigger firms (see Mean firm size row), who pay larger wages (see Mean wage row) to both male and female workers, employ higher educated workers (see Fraction with high school and Degree rows), and exhibit larger gender wage gaps. This selection forces us to explain a larger gap than the one actually present, but, as shown other covariates can explain it. Another question one should answer is whether the gender wage gap our data exhibits closely follows the actual gender gap in Chile. For that, figure 1 presents a graphic evolution of the gap using public survey data gathered by *Instituto Nacional de Estadísticas* (INE). We can see that the gap increases and decreases between 2010-2016, returning to its original level, and decreases steadily from 2016 onwards. This is very similar to what we have on the Unemployment Insurance dataset. Finally, figure 1 shows that the gap fell considerably in 2020, which is because of the heterogenous pandemic and recession effects on men and women employment. This fact suggests that we should not include this data in our estimation, so we have one model (3-year period sub-samples) that drops these year's observations.

5.2 Estimation Results

In Table 11, we present the estimation results from the two-way fixed-effect model for men and women in the largest connected set of workers of each gender. The covariates included are workers and firm fixed effects, monthly dummies in levels interacted with four education categories (no education, primary, secondary and tertiary), plus quadratic and cubic age terms interacted with the education dummies. We present, complete summary of the parameter estimate for the 2010-2020 period. Table 12 shows the typical decomposition of the log wages variance between the variance in person fixed effects, firms fixed effects, the covariance between person and firm effects (sorting), the covariance of person effects and firm effects with the covariables in X, and the residual but for the sub-samples estimations. We also present the goodness of fit of the models.

Figures 1 and 6 present the evolution over time of these decomposition, for men and women, respectively.

6 Firm-specific Pay Premiums and the Gender Wage Gap

We quantify the effect of firm-specific pay premiums using normalized firm effects for male and female workers. In Table 8 we present the results for the full period sample and the 2-year periods sub-samples, and in Table 9 we present the robustness check on 3-year periods sub-samples.

6.1 Whole period

Column (1) of Table 8 shows that the wage gap for the dual-connected set is 17 log points. It is to be noted that this wage gap is larger than the one on the original data, of 13 log points as pointed out in Table 7. Columns (2) and (3) show the male and female mean pay premiums, and column (4) shows the difference between the two, which corresponds to firms' total contribution to the wage gap. Column (5) shows the share of the gender wage gap this difference consists of, approximately 50% (9 log points) for the whole period, meaning one half of the total gender wage gap in the selected sample is due to firm specific pay policies. Next, in columns (6) to (13), we compute the terms contained in equation 7a/7b. We find that when the decomposition 7a is implemented, sorting explains 42,5 (column 7) percentage points (7 log points (column 6)) of the 50 percentage points explained by the firm, while bargaining explains the remaining 2 log points (column 12) (almost 9 percentage points (column 13). Alternatively, when we follow decomposition 7b, sorting explains 33 (column 9) percentage points (6 log points (column 8)) of the 50 percentage points explained by the firm, while bargaining explains the remaining 3 log points (column 10) (18 percentage points (column 11).

6.2 Evolution

We implement the Oaxaca-style decomposition to the estimation on sub-periods to get an insight into the evolution of the firm's contribution to the gender wage gap over time. Second to last rows in Tables 8 and 9 show the results of this exercise. Figures 2 to 5 show these results graphically.

We wanted to study this evolution with the greater detail possible, which meant performing the estimation on the more partitioned sample possible -for example, every year from 2010 to 2020 or every two years-. However, in every two-way fixed-effects analysis, the sample selection that the range condition imposes (connected and dual connected set) can be an issue threatening the external validity of results. When we narrow the time span, worker mobility becomes more binding as fewer workers move in one or two years than in ten. Therefore the connected sets restriction imposes greater limitations to the analysis as we shorten the period on which each AKM estimation is performed. In addition, the last two-year-long sub-sample in the data goes from July 2018 to June 2020, which comprehends Chile's social unrest of 2019 and the economic crisis associated with the Covid-19 pandemic. These preoccupations make us choose the three-year sub-samples decomposition as our preferred one. We perform the analysis on a two-year sub-sample specification as well to see a more detailed evolution, but keeping the two issues pointed in mind. Three-year samples are considered from September to September to maximize the available data volume not compromised by the events starting in October 2019. Table 9 presents these results. Two-year samples are considered from June to July, for the last period available was July 2020. Table 8 presents this decomposition.

We can see in both specifications that the reduction in the gender wage gap is not only not explained by a narrowing in the gender-differentiated firm-specific pay policies, but these differences show to be growing persistently over time (see Figures 2 and 3). The growth in firm's contribution to the gap is shown to be widely explained by an increase over time in the bargaining component (dark blue area on Figure 4), these results being consistent with the robustness specification (see dark bluea area on Figure 5). The bargaining channel is negative at the beginning of the time span, meaning that relative to the complete specification, at the first sub-periods, women earned larger wages than men because of receiving larger premiums at the same jobs, this differential is offset by a more significant positive sorting channel (because the firm premium differential is still positive for males in every specification), which means women end up earning lower wages because they end up matched with firms which pay lower premiums to every worker.

Table 8 shows for the 2 year sub-samples, the bargaining channel growing from between -0.03 using male distribution (first row of Sub-periods panel, column 11) and -0.05 using female distribution (column 13) of a difference in 0.09 (column 5) on premiums (19% of the gap (column 6)) up to between 0.06 using male distribution (fifth row of Sub-periods panel, column 11) and 0.04 using female distribution (column 13) of a difference of 0.11 (column 5), 56% of the gap (column 6). While the differences between male and female premiums across female or male jobs (bargaining) grow across the period, the difference in the average compensation of men and women across their job distribution decreases (sorting) from between 0.09 using male effects (first row of Sub-periods panel, column 7) and 0.07 using female effects (column 9), to between 0.06 (fifth row of Sub-periods panel, column 7) using male effects and 0.05 (column 9) using female effects, showing that women's capacity for positive sorting improves over time, but the more significant worsen of their bargaining conditions make the firms component of the gap to increase across the period.

Table 9 shows a similar evolution for the 3 year sub-samples. Bargaining channel grows from between -0.02 using male distribution (first row of Sub-periods panel, column 11) and -0.04 using female distribution (column 13) of a difference in 0.09 (column 5) on premiums (22% of the gap (column 6)) up to between 0.05 using male distribution (fifth row of Sub-periods panel, column 11) and 0.03 using female distribution (column 13) of a difference of 0.10 (column 5), 53% of the gap (column 6). Sorting decreases from between 0.09 using male effects (first row of Sub-periods panel, column 7) and 0.07 using female effects (column 9), to between 0.06 (fifth row of Sub-periods panel, column 7) using male effects and 0.05 (column 9) using female effects. The first row of the Sub-periods panel shows sorting to represent 0.09 [5] log points of a 0.05 gender premium gap (22% of the whole wage gap) and bargaining to explain -0.04 [6] of this difference, pointing that women earn higher wages when employed at the similar wage-premium firms.

[5] When looking at sorting channel calculated using male effects (column 6).

[6] When looking at bargaining using female distribution (column 13).

This specification can be directly compared to one of Cruz and Rau (2017) specifications, that performs the analysis on a 2010-2013 period. While they find positive bargaining (0.020) using the female distribution, they encountered a very similar sorting effect using male premiums (0.084). Estimates on bargaining much depend on the normalization chosen, which might explain the differences we get.

6.3 Firm size analysis

Table 10 presents the results on the decomposition for the estimation of the 3-year sample by firm size. While the analysis across all firms showed the gender gap diminishing over time, increasing importance of the firm pay policies in its determination, growth in the bargaining power channel and a decline in sorting, those results vary significantly across firm size.

For firms that hire more than 200 workers, the results are the same in sign as the cross-section. These firms face bigger penalties and are also obliged to post disclosure documents. As can be expected, because bigger firms are typically higher-paying firms, firm-specific pay premiums are larger for both men and women than at any other firm size. Also, the difference between them is more extensive, meaning firms play a larger role in determining the gender wage gap at any period at larger firms. Sorting effect is only relevant at this firm size, explaining up to a 42% of the wag gap in 2010-2013. Sorting decreases steadily, while bargaining increases in a greater magnitude, jointly raising the participation of firms in the gap. The gap is decreasing, but firm's importance is augmenting, so the result is the same as the cross-sectional analysis for big firms.

Firms that have between 50 and 200 workers and firms with 10-50 workers show a much more stable gender wage gap in time. Firms' importance is also increasing, explained by an increase in bargaining and a decrease (less significant than for larger firms) in sorting not large enough to reverse the bargaining channel increase. For firms with 10-50 workers, the evolution of sorting is even more stable.

While firms with lower than 10 workers are not affected by the law, we found that they are the ones that present the lower bargaining channel in favor of men of the first period after the law implementation. Bargaining comes to explain -117 log points of the gender wage gap in the 2010-2013 period, meaning female workers are in much better conditions to negotiate than their male co-workers. This does not imply there is no gender wage gap, for it is still positive, and is explained by other variables in our wage model (covariates, return to covariates and worker fixed effects). Firm-based pay policies do not contribute to the gender gap in smaller firms; by the opposite, they reduce it. The evolution that these firms show is, like every other firm, an increase in bargaining. The difference is that bargaining is still negative at the end of the period, favoring women's negotiation. Another issue that points out is that while sorting seems to decrease through time in every other firm size, sorting remains relatively stable for these firms. The sign is the same as every other specification. The magnitude is smaller, varying between 0.01 and 0.03, explaining up to 20% of the part firms play in determining the gender wage gap. These findings mean that while men do engage in more positive sorting than women at smaller firms, this effect is smaller than in larger firms, and it doesn't vary across the period.

In conclusion, both the gender gap and the gap between firm specific premiums earned by men and women are much larger at bigger firms. Not only does it reach higher values, but they constitute 1000% of the estimates in medium-sized companies (11 points difference on average versus 2) and small companies (11 points versus 0).

7 Policy implications

This paper does not estimate the effect of EPL. However, we show that firm-specific pay policies are more gender differentiated than 10 years ago. These findings suggest EPL must be strengthen but also, that there may be other policies that can achieve the result of reducing the firm-specific pay premium gap. Any policy that improves bargaining power or positive sorting ability for women will do.

EPL establishes that the responsibility for compliance with the principle of equal pay between men and women rests exclusively with companies. This responsibility means that (1) companies with ten or more workers must have a protocol for internal complaints of non-compliance with their Internal Regulation of Order, Hygiene and Safety, (2) companies have up to 30 days to respond to internal complaints, and (3) that if workers do not receive a response or receive one that does not satisfy them, they can report the case to the Labor Directorate or the Labor Courts, who will mediate the conflict with the objective that equal compensation is established if the complaint is found to be contingent. In addition, companies with more than 200 workers must contain a record that lists the various positions or functions in the company in their Internal Regulations.

Our article does not directly estimate the effect of EPL. However, it shows that we are worse off than we were 10 years ago in terms of what firm-specific wage policies explain. The findings reveal the need to strengthen the wage equity law. Further investigation allowed us to find three aspects in which the law proves to be weak and can improve: Enforcement, Available Information, and Fines.

The first aspect has to do with the audit of EPL. For a company to be convicted of breach of the principle of equal remuneration between a man and a woman, this must have been reported by the discriminated worker to the Labor Courts or alternatively to the *Dirección del Trabajo* (Labor Directorate); subsequently, the inspector should have mediated the dispute. If the company refused to respond, it must have been prosecuted and ultimately found guilty. However, for a worker to have the right to file a complaint against the firm in either of these two institutions, she must have first complained within her own company, as established by the company's Internal Regulations. The firm has 30 days to give a formal response, and if the company does not meet the deadline or the worker finds the response unsatisfactory, the worker can file the complaint with the supervisory body. Then, the examiner begins a process of intervention of the case, where the conflict is mediated. If the company does not comply with the agreement in the mediation, then the penalty or fine applies. Different feminist organizations have argued that it is highly improbable that a victim would dare to complain to the same organization that discriminated against her (her own company). Filing a complaint with the company itself is necessary for the audit, making it very unlikely that a company will be audited. As stated before, since the creation of the law, only 12 complaints have been made for breach of the principle of equal remuneration.

A policy proposal to make the law more effective is to carry out ex officio audits. In other words, the labor authority must periodically and randomly review compliance with the principle of equal remuneration. Ex officio examination can take place in different ways. An example is that the labor authority periodically inspects companies, but it can also be firm's own responsibility to accredit themselves as gap-free firms. This is the case with Icelandic legislation, where companies with more than 25 workers must obtain a certificate of equal pay. An alternative or complementary proposal allows the complainants to go directly to the Labor Directorate or the Labor Court to file complaints about a breach of the norm. Also, enable unions to file a complaint in place of the affected worker.

The second aspect is that the only information requirement EPL establishes is that companies with more than 200 workers must contain a record that lists the various positions and functions in the company in their Internal Regulations. If made mandatory, a measure that would facilitate inspection would be for companies to add wages to the said registry and the gender of the worker who occupies each position or function. British legislation incorporates the obligation to publish the average percentage difference in salaries by gender for those companies or organizations with more than 250 workers, which facilitates the control that their standards of equity fulfilled. Another example is Germany, a country where companies with more than 500 employees must submit periodic reports. In them, they must justify the firm ensures compliance with equal pay for male and female workers.

The third and last aspect has to do with the magnitude of the fines. According to the Inspection Department of the Labor Directorate (2021), there are three fines associated with non-compliance with the 2009 wage equity law. The three fines are directly proportional to the degree of non-compliance with the norm and the company's size, measured in the number of permanent workers in the company. A company will be fined if: (1) it does not contain the complaint process for non-compliance with the principle of equal remuneration for men and women, (2) it does not respond to a complaint within 30 days, or (3) it does not contain a record of the positions or functions and their essential characteristics and their remuneration. The fines associated with the offenses (1) and (2) are described in table 1 and the fines related to non-compliance with the rule (3) are described in table 2. Penalties are measured in Monthly Tax Units (UTM).

Table 1: Fines associated with not containing the claim process or not responding to a claim within the legal term

Firm size	Mild	Severe	Very serious
1-9 workers	3	4	5
10-49 workers	6	8	10
50-199 workers	24	32	40
200 or more workers	36	48	60

Table 2: Fines associated with not having the record of positions and functions

Firm size	Mild	Severe	Very serious
200 or more workers	36	48	60

The fine structure associated with the law suggests that it is not a bet that the principle of equal remuneration is fulfilled by the economic incentives established by the fines. Penalties are minimal: For the median income of 420 thousand CLP, a gap of 0.23 points would imply that the median women earned approximately 324 thousand. If the company hires 200 workers, the cost of eliminating its wage gap is 19 million CLP or 355 UTM. If the fines were collected (we know that this is not the case because inspection does not happen), it would be more efficient to pay the penalties and not comply with the law than to comply with the law and avoid the fines.

For this reason, establishing ex officio inspection, the possibility of direct reporting to the labor authority and more mandatory available information are not enough to strengthen EPL. In addition to the three proposals stated, fines must rise to constitute an economic disincentive to discrimination. If they stay minimal, they are nothing more than the cost to pay for not complying with the norm.

Finally, different policy proposals that can emerge from this research go beyond the gender equity law.

We find that a very important part of the gap is explained by the fact that companies can establish differentiated gender wage policies given their market power in the labor market. Then, one way to limit this possibility is to reduce the monopsonist power of employers or increase the relative market power of workers. Market power affects women's wages significantly as they have more inelastic offers, so it is necessary to develop measures that level the wage-labor supply elasticity of women to men. Examples of these are labor counterclaim and job re-conversion instances for women, training on technologies, etc. Another measure is pro-unionization policies, such as allowing bargaining by branch. Such a measure would presumably improve the wage premiums for all low-wage workers and not only for women. Nonetheless, considering that women's unionization rates are higher and that women are more likely to occupy lower-wage jobs -which are on average more likely to be covered by collective contracts-, it may also help to diminish the gender wage gap.

Our findings suggest that what explained the rise in firm effects gap was the bargaining channel. The relationship between unionization, labor market power, and the gender wage gap should be studied thoroughly, as it is likely of great interest. This investigation is pending further studies.

8 Conclusions

Since EPL's promotion in 2009, Chile's Gender Wage Gap remained constant until 2016 and witnessed a discrete diminish to date. Motivated by this evolution and the severe concerns activist and experts have about the effectiveness of EPL, we implemented a CCK decomposition of the gender wage gap between the part explained by workers characteristics and that due to firm-based pay policies. We performed the methodology on successive time windows to catch the evolution of these variables over time. This paper is the first to achieve the latter, thanks to the richness of our data.

For the 2010-2020 period, firms' total contribution accounts for a 50% (8.6 pp log points) of the 17 pp log points gap. Sorting effects account for 82 to 64% of the firm effects (8 to 7 pp log points, 42 to 30% of the 17 points gap). Bargaining effects account for 18 to 36% of the firm effects (2 to 3 pp log points, 9 to 18% of the 17 points gap). The gap is narrower in the period because the estimation sample -dual connected set- accounts for 90% of female and male workers. This is the closer the gap gets to the actual gap in the original sample, of 13 pp log points.

We found that firm-specific pay premiums are far from stable in time, as they vary for male and female workers. Female workers see their premiums getting lower through the period, starting at 8 pp log points in 2010-2013, and ending at 4 pp log points in 2016-2019. These variations make up that while the gender gap narrows on our sample from 22 pp log points to 19 pp log points, the part that pay policies' account of it increases unwaveringly over time. The firms' total contribution beggins accounting for a 22% of the 22 pp log points gap (5 pp log points) and ends up accounting for 53%, (10 pp log points). This evolution is mainly explained by an increase in the Bargaining Channel. Bargaining estimates for the 2010-2013 period are negative, meaning bargaining does not explain pay premiums in favour of male but of female workers. At this window, Bargaining accounts for between -86 to -46% of the firm effects (-4 to -2 pp log points, -18 to -10% of the 22 points gap). At the first window, the Sorting Channel is what explains that firms policies determine lower wages to women than men: female are more likely to be paired with lower surplus' firms. Here, Sorting account for between 186 to 146% of the firm effects (9 to 7 pp log points, 40 to 32% of the 22 pp log points gap). Nevertheless, Bargaining increases steadily, ending up accounting for between 35 to 54% of the firm effects (3 to 5 pp log points, 18 to 29% of the 19 points gap), while Sorting decreases more discretely, finally explaining between 65 to 46% (6 to 5 pp log points, 34 to 25% of the 19 pp log points gap) from 2016 to 2019. This evolution is even more evident for firms with 200 or more workers, who show the most significant gender wage gaps and the largest firm-specific pay premium gap between men and women.

These results do not mean to assess the impact of EPL directly. However, they are not consistent with a positive evaluation of the law. If EPL had done a great job leaving a small space for firms to pay differently to male and female workers who perform the same jobs, we would not see such essential gaps in firm-specific pay premiums. The most recent time window estimation of our main specification suggests that between 2016-2019 firms' pay policies accounted for a 53% of the 19 log points wage gap, meaning more than half of it is not due to different ability or productivity between men and women, but different pay premiums paid to them.

It is of our interest for future research to understand the links between firm-specific premiums and unionization. We want to include measures of union membership and the coverture of collective bargaining contracts and agreements to see how premiums vary across different levels of workers' bargaining power. Also, further research must comprehend the effectiveness of the vast possible policies to increase bargaining power for women in this context, relative to the effect of measures such as equal pay laws.

References

[1] Abowd, John M., Francis Kramarz, and David N. Margolis. (1999). *High Wage Workers and High Wage Firms.* Econometrica, 67(2): 251-333.

[2] Albagli, E., Chovar, A., Luttini, E., Madeira, C., Naudon, A., & Tapia, M. (2017) *Labor Market Flows: Evidence from Chile Using Micro Data from Administrative Tax Records.* Central Bank of Chile Working Papers Central Bank of Chile 812.

[3] Babcock, L. y Laschever, S. (2009). *Women don't ask: Negotiation and the gender divide.* Princeton University Press.

[4] Bassanini, A., Garnero, A. (2013) *Dismissal protection and worker flows in OECD countries: Evidence from cross-country/cross-industry data.* Labour Economics, 21: 25-41.

[5] Bertrand, M., Goldin, C., Katz, L. F. (2010). *Dynamics of the gender gap for young professionals in the financial and corporate sectors.* American economic journal: applied economics, 2(3), 228-55.

[6] Bertrand, M., Kamenica, E., Pan, J. (2015). *Gender identity and relative income within households.* The Quarterly Journal of Economics, 130(2), 571-614.

[7] Bhalotra, S., Fernandez Sierra, M. (2018). *The distribution of the gender wage gap.* Available at SSRN 3202481.

[8] Bowles, H. R., Babcock, L., Lai, L. (2007). *Social incentives for sex differences in the propensity to initiate bargaining: sometimes it does hurt to ask.* Organizational Behavior and Human Decision Processes, 103, 243-273.

[9] Berger, D., K. Herkenho , and S. Mongey (2019). *Labor market power.* Working paper.

[10] Bonhomme, S., T. Lamadon, & E. Manresa (2019). *A Distributional Framework for Matched Employer Employee Data.* Econometrica, 87, 699–739.

[11] Bruns, B.(2019) *Changes in Workplace Heterogeneity and How They Widen the Gender Wage Gap.* American Economic Journal: Applied Economics, 11(2): 74–113.

[12] Caldwell, S., Oehlsen, E. (2018). *Monopsony and the gender wage gap: Experimental evidence from the gig economy.* Massachusetts Institute of Technology Working Paper.

[13] Card, D., Cardoso, A., Heining, J., Kline, P. (2018). *Firms and Labor Market Inequality: Evidence and Some Theory.* Journal of Labor Economics 36(S1), S13-S70.

[14] Card, D., Cardoso, A. R., Kline, P. (2016). *Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women.* The Quarterly Journal of Economics, 131(2), 633-686.

[15] Casarico, A., & S. Lattanzio (2019) *What Firms Do: Gender Inequality in Linked Employer-Employee Data.* Faculty of Economics, University of Cambridge Cambridge Working Papers in Economics 1966.

[16] Coudin, E., Maillard, S. & To, M.(2018) *Family, firms and the gender wage gap in France.* Institute for Fiscal Studies IFS Working Papers W18/01.

[17] Cruz, G., & Rau, T. (2017). *The Effects of Firms and Equal Pay Laws on the Gender Wage Gap: Evidence from Chile.* Manuscript, Pontificia Universidad Católica de Chile.

[18] Departamento de Inspección, Dirección del Trabajo (2021) *Tipificador de hechos infraccionales y pauta para aplicar multas administrativas.* here.

[19] Ghosh, P. K. (2018). *A Study of the Long-run Substitutability Between Men and Women.* IZA Conference mimeo.

[20] Jarosch, G., J. Nimczik, and I. Sorkin (2019). *Granular search, market structure, and wages.* Working paper.

[21] Kline, P., R. Saggio, and M. Sølvsten (2018): *Leave-out estimation of variance components.* Working paper.

[22] Lamadon, T., M. Mogstad, and B. Setzler (2019). *Imperfect Competition, Compensating Differentials and Rent Sharing in the U.S. Labor Market.* Working paper.

[23] O'Neill, J. E., O'Neill, D. M. (2006). *What do wage differentials tell about labor market discrimination?.* Polachek, S., Chiswick, C. and H. Rapoport (eds.) Research in Labor Economics, 24, 293-360.

[24] Postel-Vinay, F. and J. M. Robin (2002). *Equilibrium wage dispersion with worker and employer heterogeneity.* Econometrica 70(6), 2295–2350.

[25] Rigdon, M. L. (2012). *An Experimental Investigation of Gender Differences in Wage Negotiations.* Available at SSRN 2165253.

[26] Rojas Miño, I. (2021). *El derecho de igual remuneración por igual trabajo entre mujeres y hombres ante los tribunales de justicia.* Revista de derecho (Concepción), 89(249), 15-46.

[27] Sanchez, R., Finot, J., Villena, M. G. (2019). *Gender Wage Gap and Firm Market Power: Evidence from Chile.*

[28] Sorkin, I. (2018). *Ranking firms using revealed preference.* Quarterly Journal of Economics 133(3), 1331–1393.

[29] Sorkin, I. (2017) *The Role of Firms in Gender Earnings Inequality: Evidence from the United States.* American Economic Review, 107(5): 384–87.

[30] Taber, C. and R. Vejlin (2018). *Estimation of a roy/search/compensating differentials model of the labor market.* Working paper.

9 Appendix

List of Figures

Table 3: Connected set's observations for full period model and 2-year sub-periods models

	Males					Females				
N° of:	Full sample	Largest CS	%	Dual CS	%	Full sample	Largest CS	%	Dual CS	%
Full period										
2010-2020										
p-m obs	54.599.208	53.369.409	98%	45.764.017	84%	32.542.616	31.303.424	96%	28.894.977	89%
workers	967.890	930.405	96%	871.856	90%	708.300	666.677	94%	643.057	91%
firms	370.251	330.850	89%	125.605	34%	248.884	204.841	82%	125.605	50%
Sub-periods										
2010-2012										
p-m obs	9.554.474	8.620.132	90%	6.502.736	68%	5.136.418	4.371.944	85%	3.902.863	76%
workers	606.881	546.039	90%	454.377	75%	365.117	310.099	85%	289.267	79%
firms	155.114	103.412	67%	30.258	20%	98.758	52.332	53%	30.258	31%
2012-2014										
p-m obs	10.364.920	9.365.122	90%	7.209.053	70%	5.920.272	5.059.876	85%	4.522.822	76%
workers	647.005	579.209	90%	484.185	75%	409.041	347.604	85%	322.405	79%
firms	162.217	105.843	65%	31.533	19%	105.605	54.718	52%	31.533	30%
2014-2016										
p-m obs	10.440.477	9.339.801	89%	7.139.709	68%	6.360.409	5.401.380	85%	4.809.725	76%
workers	662.797	584.449	88%	481.995	73%	432.289	362.245	84%	333.944	77%
firms	169.034	105.391	62%	31.033	18%	111.803	54.658	49%	31.033	28%
2016-2018										
p-m obs	10.865.180	9.603.307	88%	7.296.887	67%	6.852.640	5.726.105	84%	5.092.731	74%
workers	694.187	606.742	87%	497.248	72%	457.641	378.168	83%	347.517	76%
firms	180.857	110.122	61%	32.101	18%	121.087	57.158	47%	32.101	27%
2018-2020										
p-m obs	11.359.361	9.846.473	87%	7.396.923	65%	7.231.979	5.883.144	81%	5.234.376	72%
workers	706.091	606.682	86%	489.536	69%	464.888	374.063	80%	343.488	74%
firms	183.393	105.473	58%	28.902	16%	123.249	51.990	42%	28.902	23%

Table 4: Connected set's statistics for full period model and 2-year sub-periods models

	Males			Females		
	Full sample	Largest CS	Dual CS	Full sample	Largest CS	Dual CS
Full period						
2010-2020						
Mean age	38,1	37,9	37,7	37,0	36,8	36,8
Fraction < 30	29,8	30,1	30,8	32,5	33,0	33,0
Fraction > 50	18,6	18,2	17,5	14,9	14,3	14,3
Fraction with high school	62,7	62,6	62,9	65,5	65,4	65,3
Fraction with degree	9,4	9,5	10,2	12,6	12,8	12,7
Mean wage	13,545	13,556	13,619	13,417	13,428	13,448
Mean firm size	5,4	5,5	6,0	5,6	5,8	6,1
Sub-periods						
2010-2012						
Mean age	37,1	36,7	36,3	35,7	35,3	35,3
Fraction < 30	32,3	33,6	34,8	36,4	38,2	38,0
Fraction > 50	15,5	14,6	13,6	11,2	10,3	10,2
Fraction with high school	59,7	59,6	60,3	64,0	63,7	63,7
Fraction with degree	9,9	10,2	11,5	14,2	14,6	14,2
Mean wage	13,236	13,276	13,365	13,097	13,129	13,147
Mean firm size	5,3	5,7	6,5	5,6	6,2	6,6
2012-2014						
Mean age	37,6	37,2	36,9	36,3	35,9	35,9
Fraction < 30	31,1	32,3	33,1	34,3	35,9	35,7
Fraction > 50	17,3	16,3	15,5	13,1	12,2	12,1
Fraction with high school	60,1	60,7	61,4	63,9	63,8	63,9
Fraction with degree	9,8	10,0	11,0	13,5	13,7	13,4
Mean wage	13,453	13,492	13,575	13,289	13,318	13,336
Mean firm size	5,5	5,8	6,6	5,6	6,2	6,6
2014-2016						
Mean age	38,2	37,8	37,5	37,0	36,7	36,7
Fraction < 30	29,6	30,8	31,3	32,3	33,6	33,3
Fraction > 50	19,2	18,1	17,3	15,1	14,3	14,3
Fraction with high school	61,9	62,1	62,6	64,6	64,5	64,6
Fraction with degree	9,6	9,8	10,7	12,8	13,0	12,6
Mean wage	13,695	13,727	13,802	13,539	13,562	13,580
Mean firm size	5,5	5,9	6,6	5,7	6,3	6,7
2016-2018						
Mean age	38,6	38,2	38,0	37,6	37,3	37,4
Fraction < 30	28,5	29,6	29,9	30,6	31,7	31,3
Fraction > 50	20,5	19,4	18,6	16,9	16,0	16,1
Fraction with high school	64,2	64,4	64,6	66,2	66,1	66,1
Fraction with degree	9,2	9,3	10,2	11,9	12,0	11,7
Mean wage	13,602	13,638	13,717	13,470	13,500	13,519
Mean firm size	5,4	5,8	6,6	5,7	6,3	6,7
2018-2020						
Mean age	38,9	38,5	38,4	38,0	37,7	37,8
Fraction < 30	27,2	28,1	28,0	29,0	29,8	29,4
Fraction > 50	20,8	19,8	19,2	17,5	16,7	16,9
Fraction with high school	67,0	67,1	67,0	68,3	68,0	67,9
Fraction with degree	8,6	8,7	9,7	10,8	10,9	10,6
Mean wage	13,756	13,796	13,878	13,636	13,672	13,689
Mean firm size	5,4	5,9	6,7	5,7	6,4	6,8

Table 5: Connected set's observations for 3-year sub-periods models

	Males					Females				
N° of:	Full sample	Largest CS	%	Dual CS	%	Full sample	Largest CS	%	Dual CS	%
Sub-periods										
2010-2013										
p-m obs	15.387.371	14.356.882	93%	11.367.318	74%	8.454.217	7.562.650	89%	6.819.522	81%
workers	675.398	626.001	93%	548.019	81%	432.549	384.385	89%	362.579	84%
firms	187.943	142.413	76%	46.069	25%	121.777	77.615	64%	46.069	38%
2013-2016										
p-m obs	16.014.032	14.900.136	93%	11.920.725	74%	9.658.055	8.645.664	90%	7.814.216	81%
workers	712.997	652.730	92%	567.133	80%	477.130	420.054	88%	394.042	83%
firms	195.847	142.221	73%	46.045	24%	129.596	78.185	60%	46.045	36%
2016-2019										
p-m obs	17.085.860	15.693.834	92%	12.415.306	73%	10.808.289	9.513.012	88%	8.578.363	79%
workers	765.932	692.669	90%	593.784	78%	519.103	448.407	86%	418.697	81%
firms	218.149	153.384	70%	48.745	22%	147.608	84.827	57%	48.745	33%

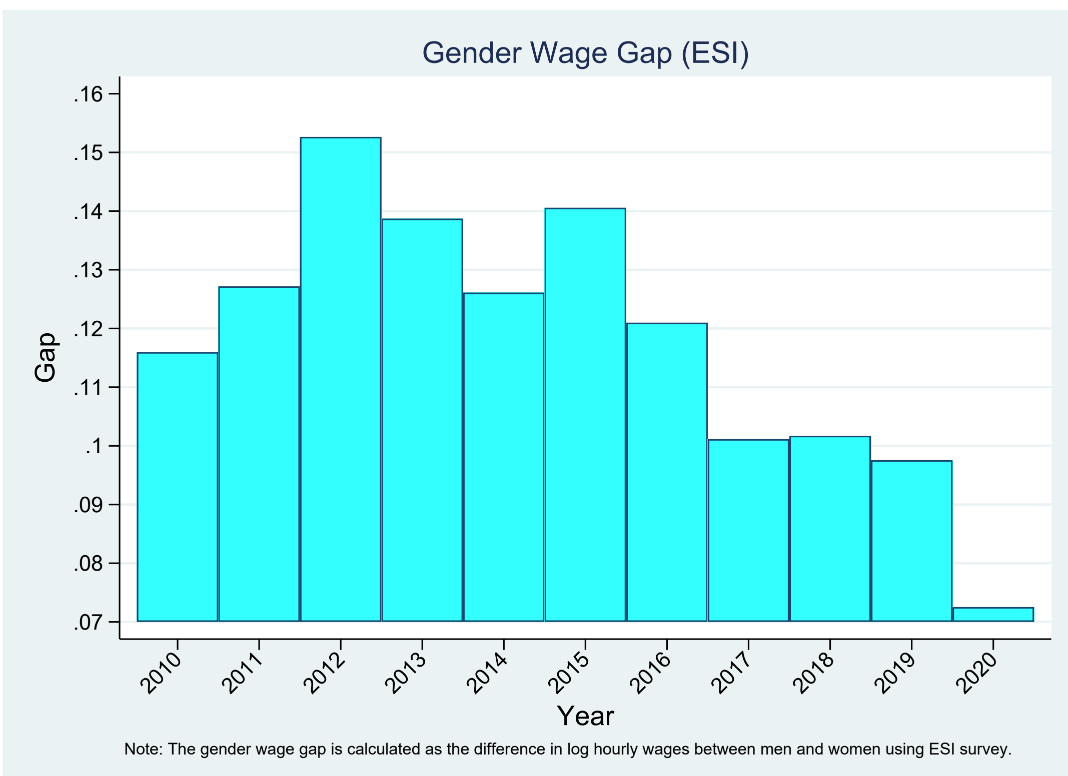
Table 6: Connected set's statistics for 3-year sub-periods models

	Males			Females		
	Full sample	Largest CS	Dual CS	Full sample	Largest CS	Dual CS
Sub-periods						
2010-2013						
Mean age	37,3	36,9	36,6	36,0	35,6	35,6
Fraction < 30	31,9	32,9	34,0	35,7	37,1	37,0
Fraction > 50	16,2	15,4	14,5	12,0	11,1	11,0
Fraction with high school	60,0	60,0	60,6	64,0	63,8	63,7
Fraction with degree	9,8	10,1	11,1	13,9	14,2	14,0
Mean wage	13,281	13,311	13,397	13,129	13,156	13,176
Mean firm size	5,4	5,6	6,4	5,6	6,0	6,4
2013-2016						
Mean age	38,1	37,8	37,5	36,9	36,6	36,6
Fraction < 30	29,9	30,8	31,4	32,7	33,8	33,6
Fraction > 50	18,9	18,0	17,2	14,8	14,0	14,0
Fraction with high school	61,7	61,8	62,3	64,5	64,5	64,5
Fraction with degree	9,7	9,8	10,7	13,0	13,2	12,9
Mean wage	13,675	13,698	13,771	13,518	13,537	13,556
Mean firm size	5,5	5,7	6,4	5,7	6,1	6,5
2016-2019						
Mean age	38,7	38,4	38,2	37,7	37,4	37,5
Fraction < 30	28,2	29,0	29,3	30,2	31,2	30,8
Fraction > 50	20,5	19,6	19,0	17,1	16,2	16,4
Fraction with high school	65,3	65,4	65,5	67,0	66,9	66,8
Fraction with degree	9,0	9,1	10,0	11,5	11,7	11,4
Mean wage	13,661	13,687	13,763	13,534	13,557	13,578
Mean firm size	5,4	5,7	6,4	5,7	6,2	6,5

Table 7: Gender Wage Gap Across Samples

	Gender Wage Gap		
	Full sample	Largest CS	Dual CS
Full period			
2010-2020	0,13	0,13	0,17
Sub-periods			
2010-2012	0,14	0,15	0,22
2012-2014	0,16	0,17	0,24
2014-2016	0,16	0,17	0,22
2016-2018	0,13	0,14	0,20
2018-2020	0,12	0,12	0,19
Sub-periods			
2010-2013	0,15	0,16	0,22
2013-2016	0,16	0,16	0,21
2016-2019	0,13	0,13	0,19

Figure 1: Gender Wage Gap by Year, based on INE's anual survey on earnings (ESI)



	Gender wage gap	Male premium among men $E(\varphi_j^M\|M)$	Female premium among women $E(\varphi_j^F\|F)$	Difference and its contribution to the gap $E(\varphi_j^M\|M) - E(\varphi_j^F\|F)$		Decomposition of firm contribution component							
						Sorting				Bargaining			
						Using male effects $E(\varphi_j^F\|M) - E(\varphi_j^F\|F)$		Using female effects $E(\varphi_j^M\|M) - E(\varphi_j^M\|F)$		Using male distribution $E(\varphi_j^M - \varphi_j^F\|M)$		Using female distribution $E(\varphi_j^M - \varphi_j^F\|F)$	
Full period													
2010-2020	0,17	0,16	0,08	0,09	50,49	0,07	41,50	0,06	32,46	0,03	18,03	0,02	8,99
Sub-periods													
2010-2012	0,22	0,11	0,07	0,04	18,57	0,09	40,46	0,07	30,30	-0,03	-11,72	-0,05	-21,88
2012-2014	0,24	0,12	0,07	0,05	22,89	0,09	39,12	0,07	30,71	-0,02	-7,82	-0,04	-16,24
2014-2016	0,22	0,12	0,06	0,05	24,51	0,08	36,84	0,07	29,90	-0,01	-5,39	-0,03	-12,33
2016-2018	0,20	0,13	0,05	0,08	39,55	0,07	35,92	0,05	25,07	0,03	14,48	0,01	3,64
2018-2020	0,19	0,12	0,02	0,11	55,99	0,06	32,32	0,05	24,86	0,06	31,13	0,04	23,67

Table 8: Firm contribution and it's decomposition using 2-year sub-periods

	Gender wage gap	Male premium among men $E(\varphi_j^M\|M)$	Female premium among women $E(\varphi_j^F\|F)$	Difference and its contribution to the gap $E(\varphi_j^M\|M) - E(\varphi_j^F\|F)$		Decomposition of firm contribution component							
						Sorting				Bargaining			
						Using male effects $E(\varphi_j^F\|M) - E(\varphi_j^F\|F)$		Using female effects $E(\varphi_j^M\|M) - E(\varphi_j^M\|F)$		Using male distribution $E(\varphi_j^M - \varphi_j^F\|M)$		Using female distribution $E(\varphi_j^M - \varphi_j^F\|F)$	
Full period													
2010-2020	0,17	0,16	0,08	0,09	50,49	0,07	41,50	0,06	32,46	0,03	18,03	0,02	8,99
Sub-periods													
2010-2013	0,22	0,13	0,08	0,05	21,78	0,09	40,43	0,07	31,78	-0,02	-10,00	-0,04	-18,66
2013-2016	0,21	0,14	0,07	0,07	31,62	0,08	38,71	0,07	31,47	0,00	0,15	-0,02	-7,09
2016-2019	0,19	0,14	0,04	0,10	53,26	0,06	34,82	0,05	24,72	0,05	28,54	0,03	18,45

Table 9: Firm contribution and it's decomposition using 3-year sub-periods

Table 10: Firm contribution and it's decomposition using 3-year sub-periods, by Firm Size

Firm size	Gender wage gap	Male premium among men	Female premium among women	Difference and its contribution to the gap		Decomposition of firm contribution component							
						Sorting				Bargaining			
						Using male effects		Using female effects		Using male distribution		Using female distribution	
+200 workers													
2010-2013	0,29	0,19	0,10	0,09	31,43	0,12	42,64	0,11	35,97	-0,01	-4,55	-0,03	-11,21
2013-2016	0,27	0,20	0,09	0,10	38,38	0,11	41,60	0,10	35,10	0,01	3,28	-0,01	-3,22
2016-2019	0,24	0,19	0,06	0,13	54,07	0,09	38,02	0,07	29,60	0,06	24,48	0,04	16,06
50-200 workers													
2010-2013	0,12	0,08	0,09	-0,01	-5,27	0,04	33,28	0,02	19,85	-0,03	-25,12	-0,04	-38,56
2013-2016	0,13	0,09	0,06	0,02	18,81	0,04	30,43	0,03	23,94	-0,01	-5,12	-0,01	-11,62
2016-2019	0,10	0,10	0,03	0,07	65,32	0,03	27,10	0,01	14,04	0,05	51,27	0,04	38,22
10-50 workers													
2010-2013	0,09	-0,02	0,02	-0,04	-50,76	0,02	23,68	0,00	-0,47	-0,04	-50,29	-0,06	-74,44
2013-2016	0,11	-0,02	0,00	-0,01	-12,70	0,03	24,31	0,01	9,77	-0,02	-22,46	-0,04	-37,01
2016-2019	0,09	0,00	-0,03	0,03	31,07	0,01	17,57	0,00	-4,97	0,03	36,04	0,01	13,50
-10 workers													
2010-2013	0,08	-0,14	-0,06	-0,08	-102,06	0,01	15,46	-0,01	-19,53	-0,06	-82,53	-0,09	-117,52
2013-2016	0,12	-0,10	-0,06	-0,04	-34,33	0,03	22,45	-0,01	-5,15	-0,03	-29,18	-0,07	-56,78
2016-2019	0,09	-0,09	-0,09	0,01	7,33	0,02	22,00	-0,02	-19,32	0,03	26,65	-0,01	-14,68

Figure 2: Evolution of the gender wage gap and firm's total contribution (3 years sub-samples)

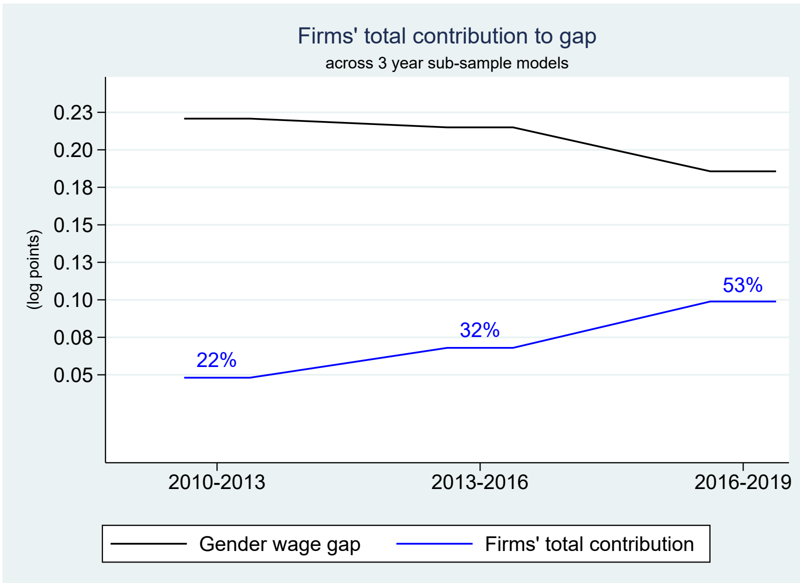


Figure 3: Evolution of the gender wage gap and firm's total contribution (2 years sub-samples)

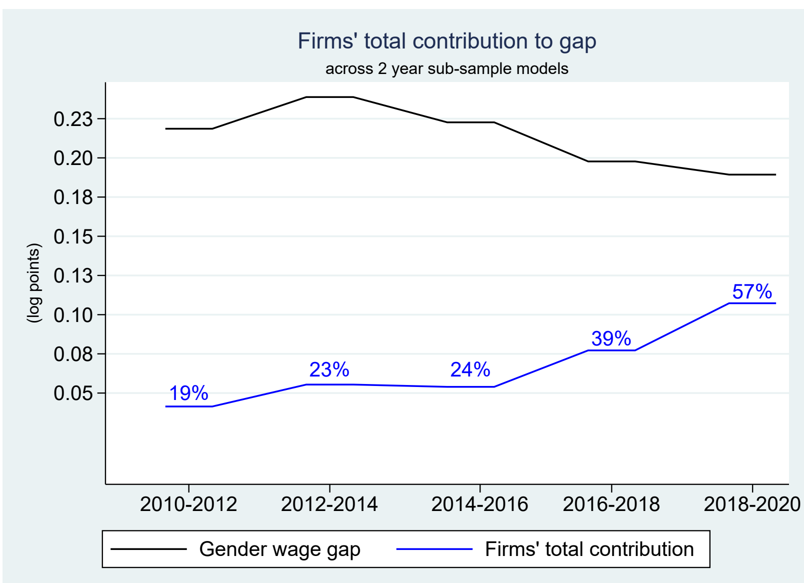


Figure 4: Evolution of the gender wage gap, firm's contribution and its decomposition (3 years sub-samples)

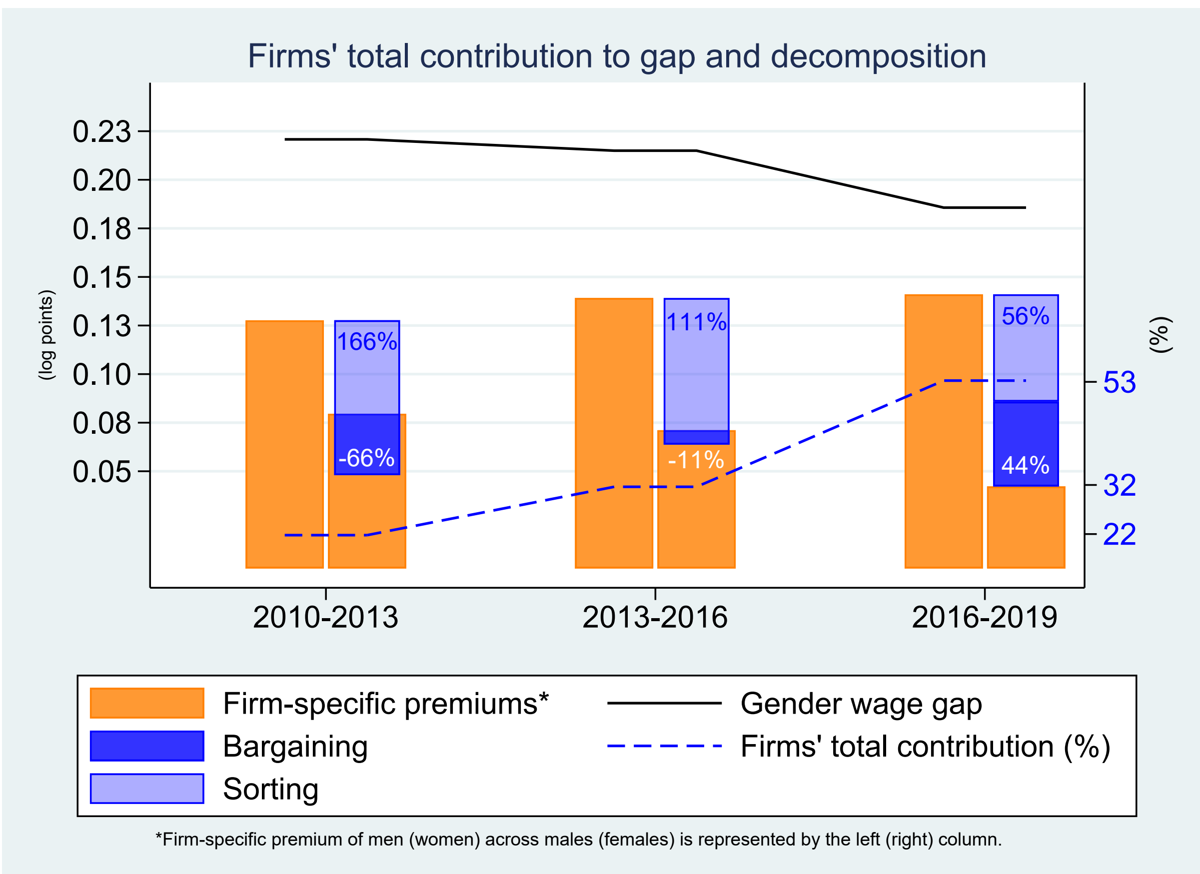


Figure 5: Firm's contribution and its decomposition (2 years sub-samples)

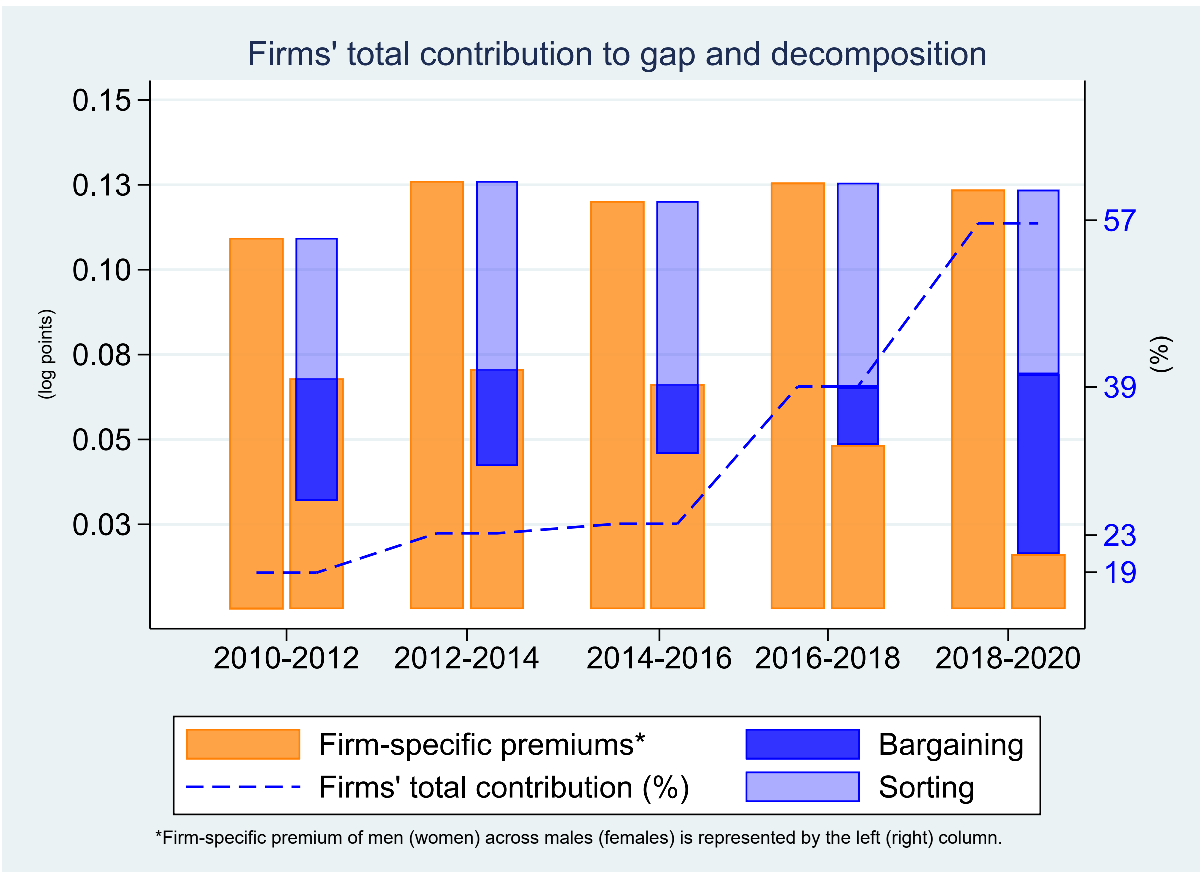


Table 11: Summary of Estimated Two-way Fixed Effects Models for Male and Female Workers

	All Males (1)	All Females (2)
Standard deviation of log wages	0.736	0.698
Number of person-month observations	53,369,408	31,303,424
Summary of Parameter Estimates		
Number of person effects	930,405	666,677
Number of firm effects	330,850	204,841
Std. dev. of person effects (across person-month obs.)	0.459	0.487
Std. dev. of firm effects (across person-month obs.)	0.294	0.221
Std. dev. of Xb (across person-month obs.)	0.353	0.351
Correlation of person/firm effects	0.246	0.187
RMSE of model	0.237	0.219
Adjusted R-squared of model	0.897	0.902
Inequality decomposition of two-way fixed effects model		
Share of variance of log wages due to:		
person effects	38.9	48.7
firm effects	16.0	10.1
covariance of person and firm effects	12.3	8.3
XB and associated covariances	22.8	23.4
residual	10.1	9.6

Note: See text. Models include dummies for individual workers and individual firms, month dummies interacted with education dummies, and quadratic and cubic terms in age interacted with education dummies.

Table 12: Summary of Estimated Two-way Fixed Effects Models for Male and Female Workers for the Sub-samples

	Var(w)		Person effects		Firm effects		Sorting		$X\beta$ & covariances		Residual		R^2		$\tilde{R}^2$	
	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females
Full period																
2010-2020	0,542	0,487	38,86	48,68	15,99	10,06	12,29	8,28	22,75	23,42	10,11	9,57	89,9%	90,4%	89,6%	90,2%
Sub-periods																
2010-2012	0,504	0,463	52,35	64,42	15,33	10,43	10,43	3,48	14,15	14,64	7,75	7,04	92,2%	93,0%	91,6%	92,3%
2012-2014	0,572	0,524	45,04	55,77	14,44	8,96	7,88	2,98	25,79	26,34	6,85	5,96	93,1%	94,0%	92,6%	93,5%
2014-2016	0,505	0,455	49,86	61,94	15,55	10,32	7,87	1,78	19,59	19,49	7,13	6,47	92,9%	93,5%	92,3%	93,0%
2016-2018	0,465	0,413	54,65	66,56	15,58	11,56	8,11	0,41	14,40	14,63	7,26	6,83	92,7%	93,2%	92,2%	92,6%
2018-2020	0,465	0,413	53,90	65,59	15,49	12,12	7,91	-0,18	15,57	15,63	7,12	6,83	92,9%	93,2%	92,3%	92,6%
Sub-periods																
2010-2013	0,540	0,494	45,76	56,76	15,48	9,58	11,51	6,62	19,18	19,81	8,08	7,24	91,9%	92,8%	91,5%	92,3%
2013-2016	0,497	0,445	47,79	60,29	16,15	10,31	9,81	4,53	18,07	17,40	8,18	7,47	91,8%	92,5%	91,4%	92,1%
2016-2019	0,463	0,410	51,66	63,06	15,63	11,14	10,37	3,76	14,47	14,51	7,87	7,54	92,1%	92,5%	91,7%	92,0%

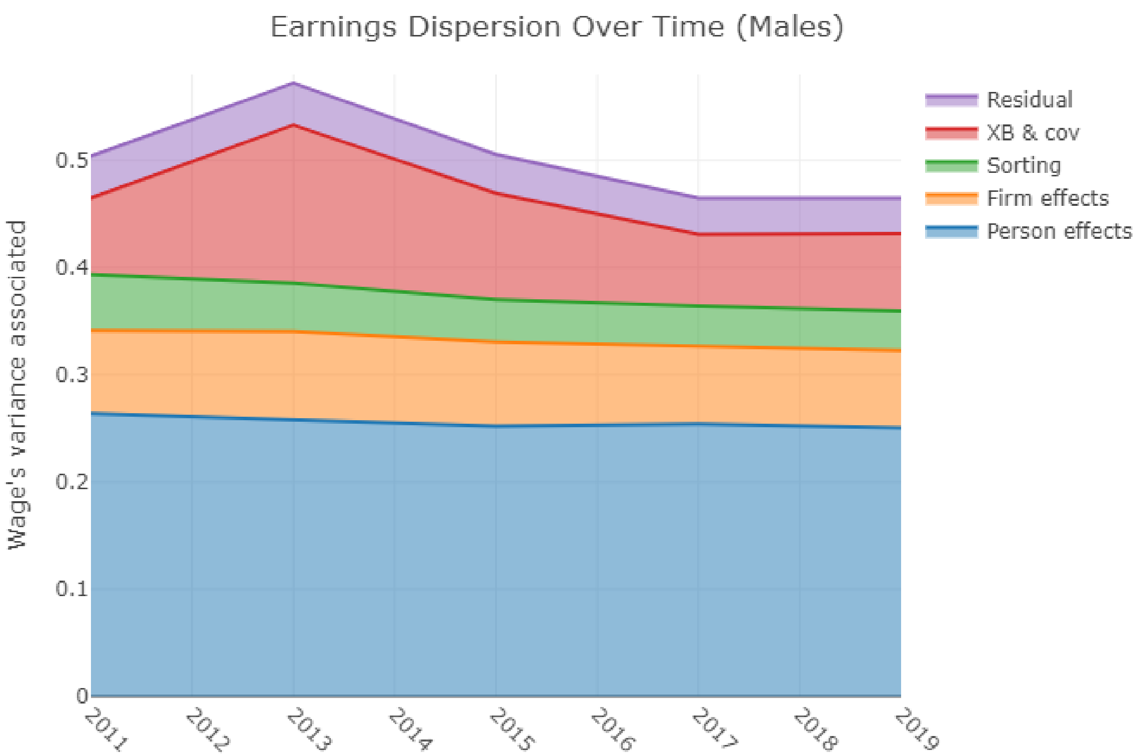


Figure 6: Part of Wage's Variance Explained by Person Effects, Firm Effects and Sorting in Time (Males)

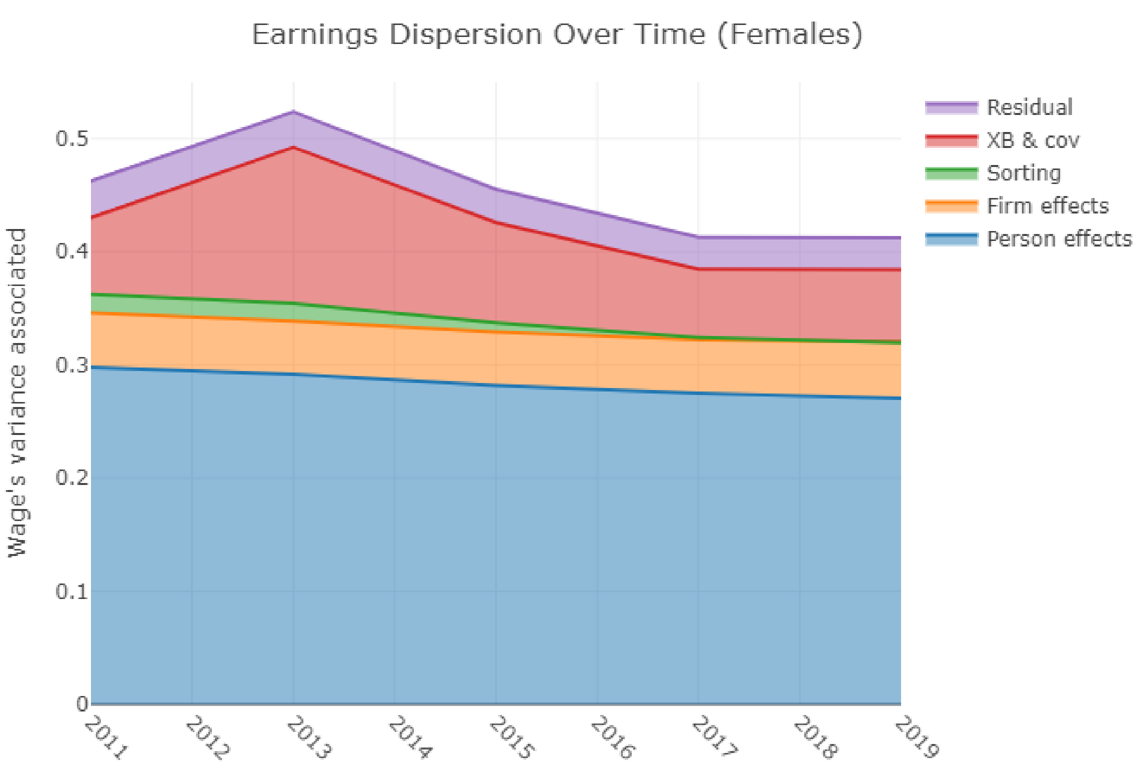
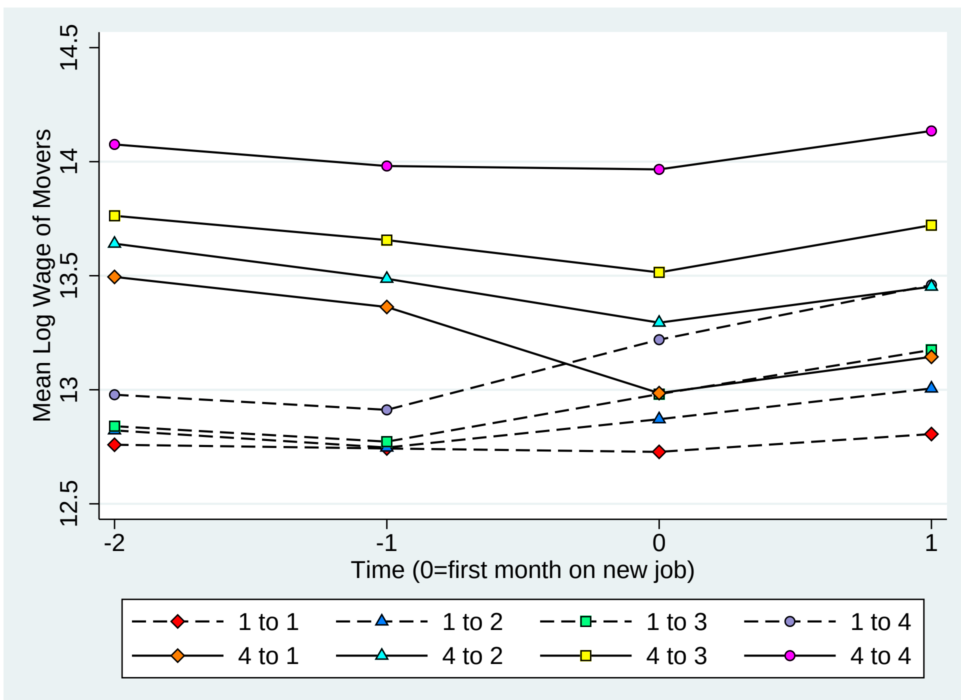


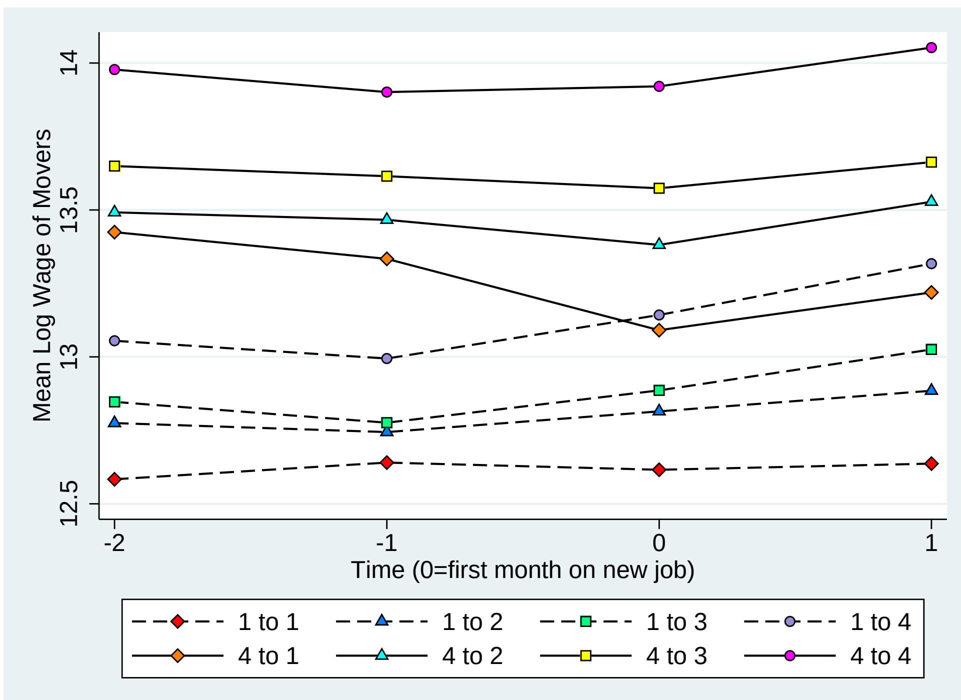
Figure 7: Part of Wage's Variance Explained by Person Effects, Firm Effects and Sorting in Time (Females)

Figure 8: Mean Log Wages of Male Job Changers, Classified by Quartile of Mean Worker Wage at Origin and Destination Firm 2010-2020



Note: figure shows mean wages of male workers at mixed-gender firms who changed jobs in 2010-2020 and held preceding job for 2 or more months, and new job for two or more months. Each job is classified into quartiles based on mean log wage at of workers of both genders of the firm in the last month of the old job (for origin firm) and the first month on the new job (for the destination firm).

Figure 9: Mean Log Wages of Female Job Changers, Classified by Quartile of Mean Worker Wage at Origin and Destination Firm 2010-2020



Note: figure shows mean wages of female workers at mixed-gender firms who changed jobs in 2010-2020 and held preceding job for 2 or more months, and new job for two or more months. Each job is classified into quartiles based on mean log wage at of workers of both genders of the firm in the last month of the old job (for origin firm) and the first month on the new job (for the destination firm).

Figure 10: Mean Log Wages of Male Job Changers, Classified by Quartile of Mean Worker Wage at Origin and Destination Firm 2010-2013

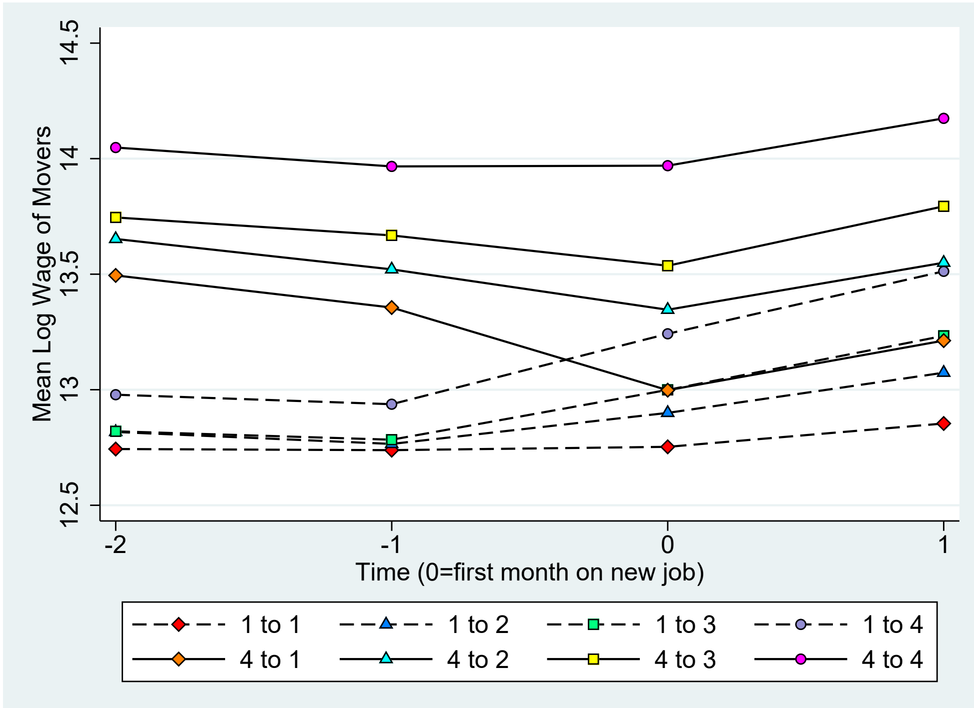
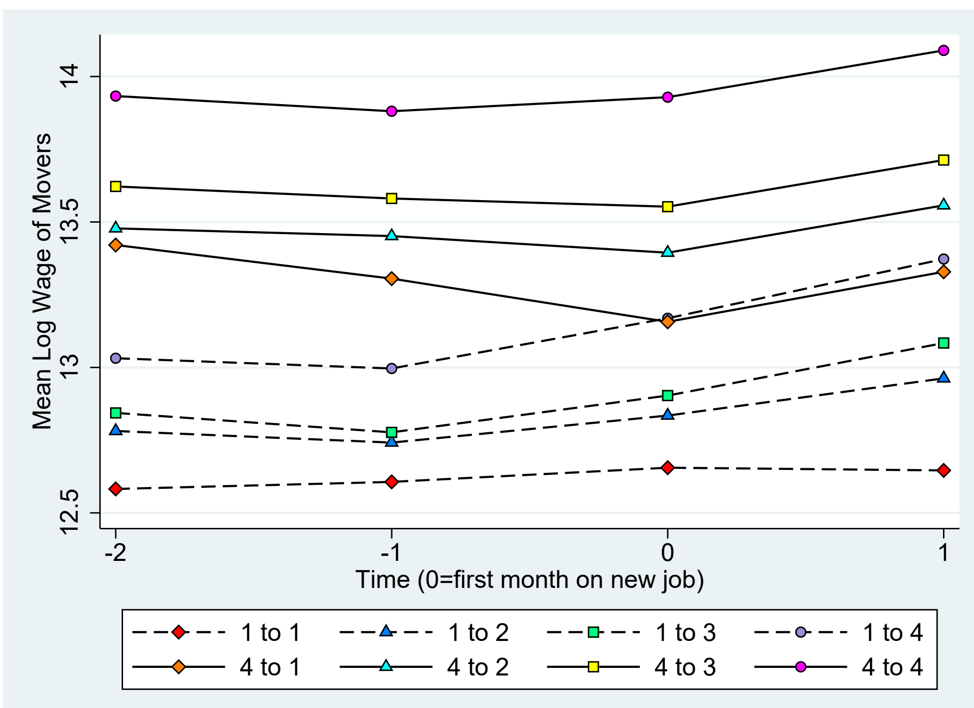


Figure 11: Mean Log Wages of Female Job Changers, Classified by Quartile of Mean Worker Wage at Origin and Destination Firm 2010-2013



Note: top (bottom) figure shows mean wages of male (female) workers at mixed-gender firms who changed jobs in 2010-2013, held preceding job for 2 or more months, and new job for two or more months. Each job is classified into quartiles based on mean log wage at of workers of both genders of the firm in the last month of the old job (for origin firm) and the first month on the new job (for the destination firm).

Figure 12: Mean Log Wages of Male Job Changers, Classified by Quartile of Mean Worker Wage at Origin and Destination Firm 2013-2016

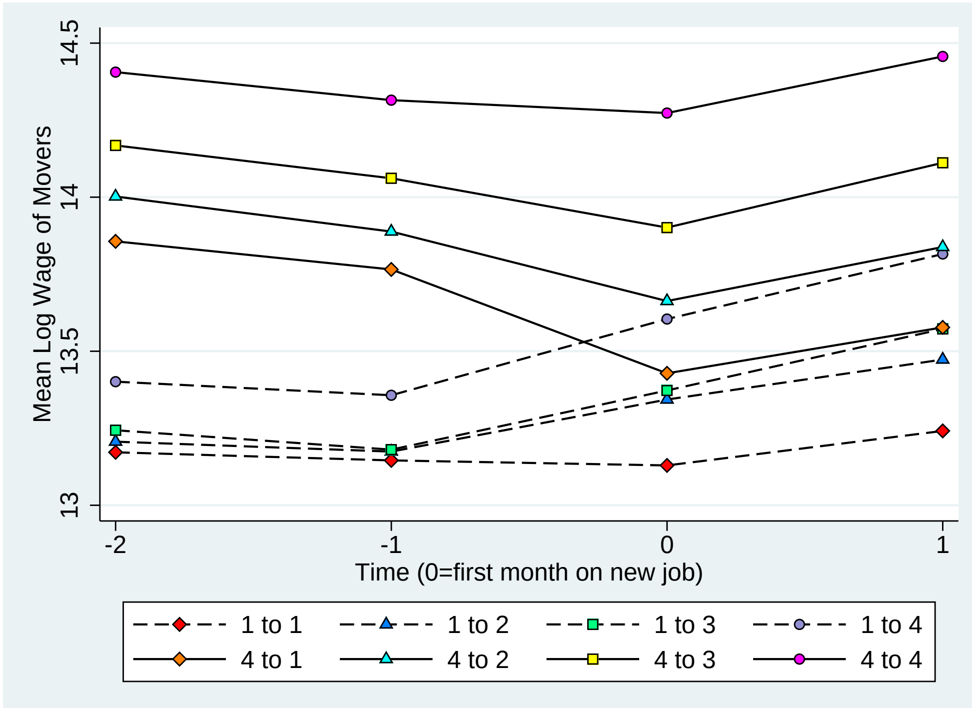
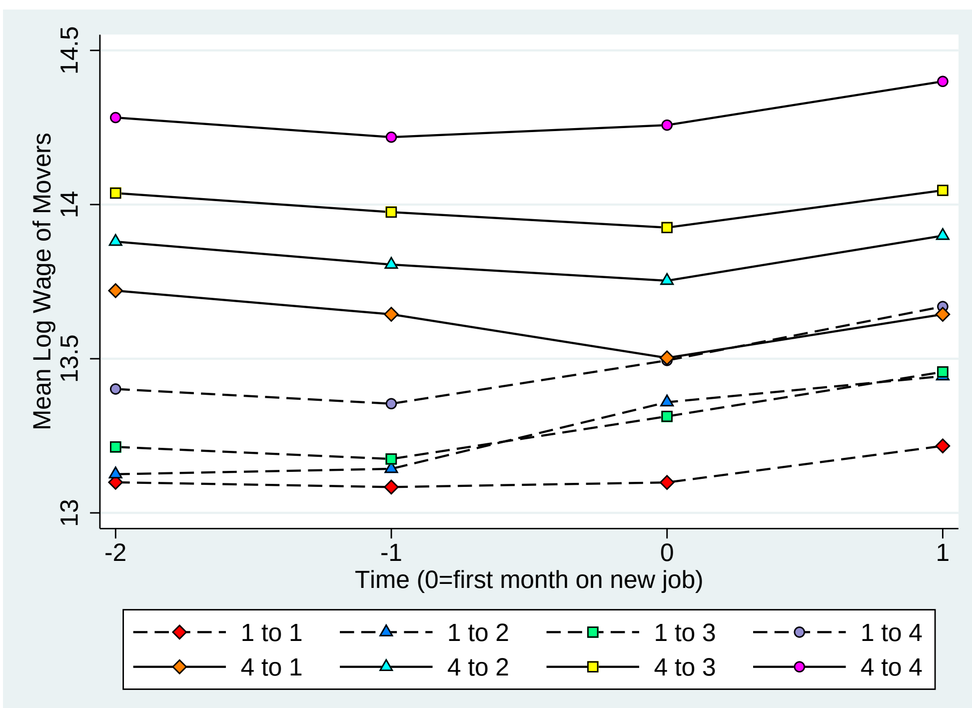


Figure 13: Mean Log Wages of Female Job Changers, Classified by Quartile of Mean Worker Wage at Origin and Destination Firm 2013-2016



Note: top (bottom) figure shows mean wages of male (female) workers at mixed-gender firms who changed jobs in 2013-2016, held preceding job for 2 or more months, and new job for two or more months. Each job is classified into quartiles based on mean log wage at of workers of both genders of the firm in the last month of the old job (for origin firm) and the first month on the new job (for the destination firm).

Figure 14: Mean Log Wages of Male Job Changers, Classified by Quartile of Mean Worker Wage at Origin and Destination Firm 2016-2019

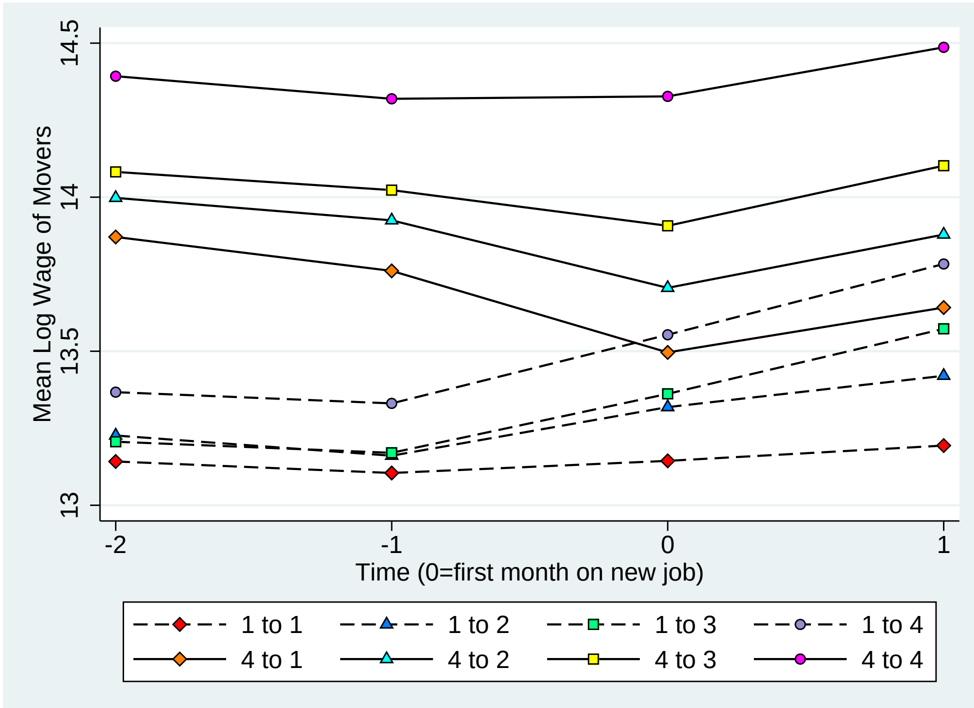
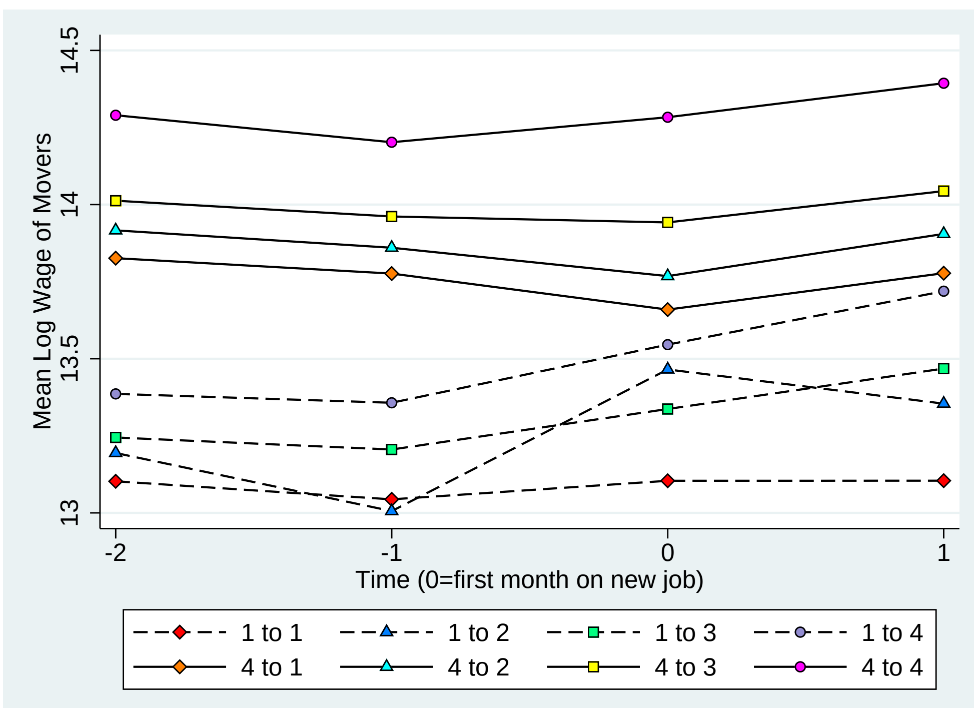


Figure 15: Mean Log Wages of Female Job Changers, Classified by Quartile of Mean Worker Wage at Origin and Destination Firm 2016-2019



Note: top (bottom) figure shows mean wages of male (female) workers at mixed-gender firms who changed jobs in 2016-2019, held preceding job for 2 or more months, and new job for two or more months. Each job is classified into quartiles based on mean log wage at of workers of both genders of the firm in the last month of the old job (for origin firm) and the first month on the new job (for the destination firm).

Figure 16: Mean Log Wages of Male Job Changers, by Quartile of Mean Wage at Origin and Destination Firm 2010-2012

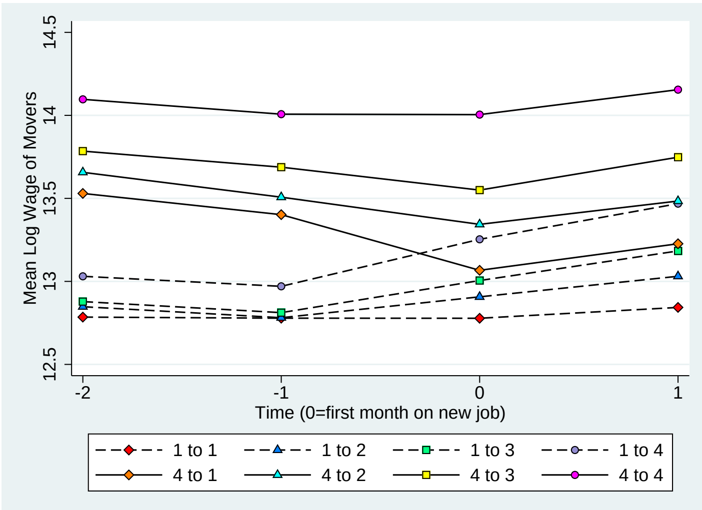
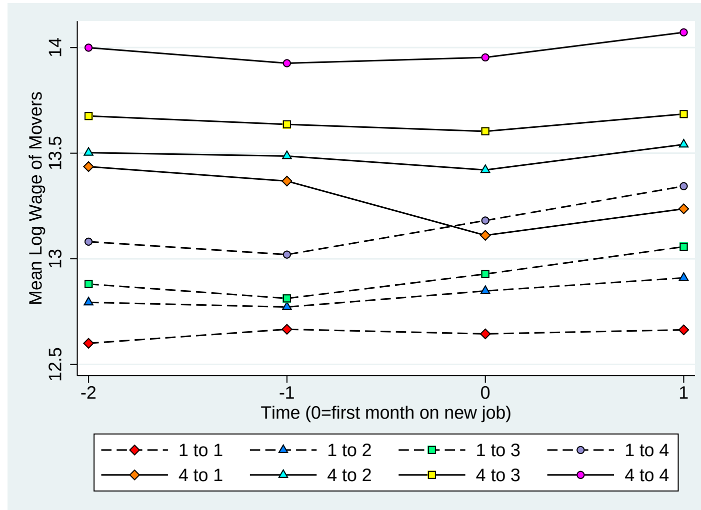


Figure 17: Mean Log Wages of Female Job Changers, by Quartile of Mean Wage at Origin and Destination Firm 2010-2012



Note: left (right) figure shows mean wages of male (female) workers at mixed-gender firms who changed jobs in 2010-2012 and held preceding job for 2 or more months, and new job for two or more months. Each job is classified into quartiles based on mean log wage of workers of both genders at the firm in the last month of the old job (for origin firm) and the first month on the new job (for the destination firm).

Figure 18: Mean Log Wages of Male Job Changers, by Quartile of Mean Wage at Origin and Destination Firm 2012-2014

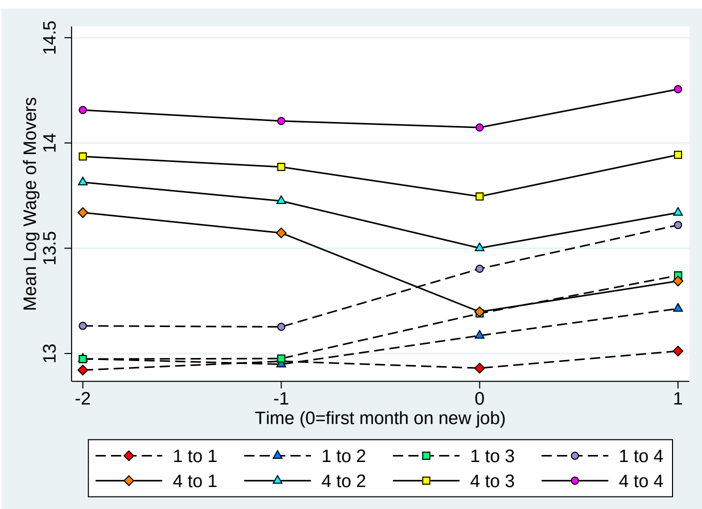
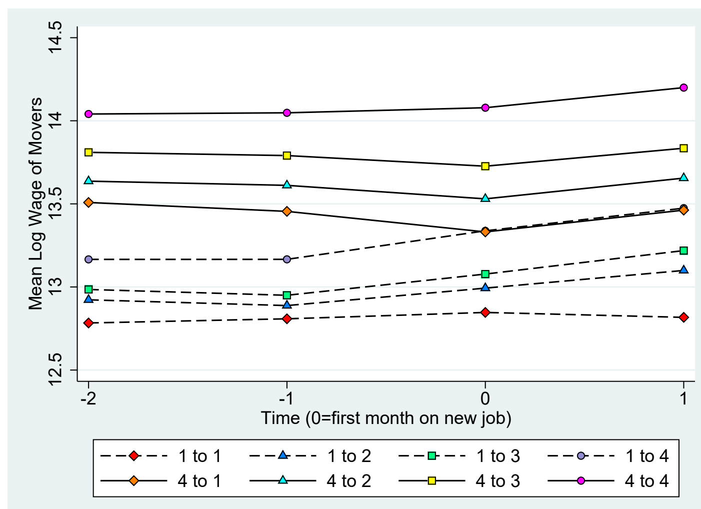


Figure 19: Mean Log Wages of Female Job Changers, by Quartile of Mean Wage at Origin and Destination Firm 2012-2014



Note: left (right) figure shows mean wages of male (female) workers at mixed-gender firms who changed jobs in 2012-2014 and held preceding job for 2 or more months, and new job for two or more months. Each job is classified into quartiles based on mean log wage of workers of both genders at the firm in the last month of the old job (for origin firm) and the first month on the new job (for the destination firm).

Figure 20: Mean Log Wages of Male Job Changers, by Quartile of Mean Wage at Origin and Destination Firm 2014-2016

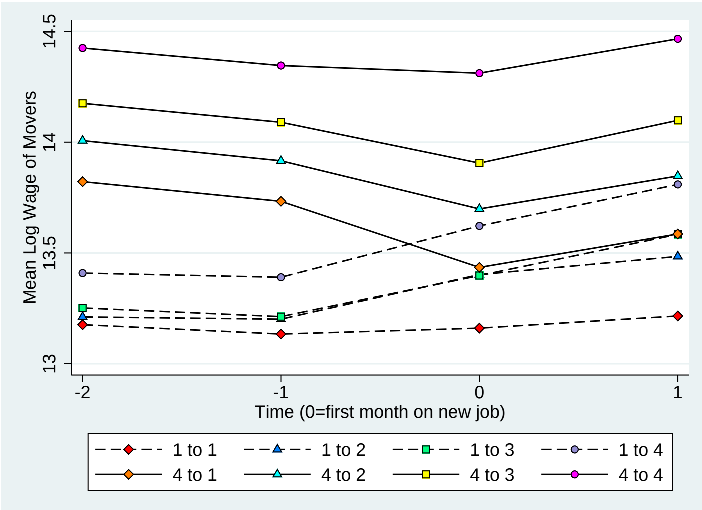
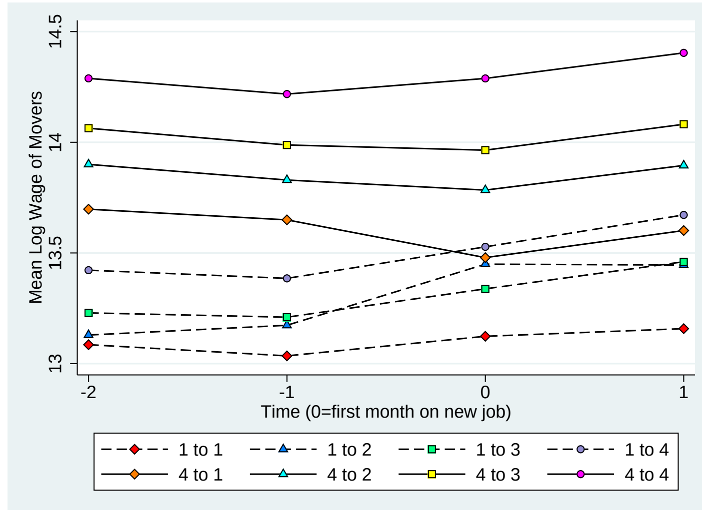


Figure 21: Mean Log Wages of Female Job Changers, by Quartile of Mean Wage at Origin and Destination Firm 2014-2016



Note: left (right) figure shows mean wages of male (female) workers at mixed-gender firms who changed jobs in 2014-2016 and held preceding job for 2 or more months, and new job for two or more months. Each job is classified into quartiles based on mean log wage of workers of both genders at the firm in the last month of the old job (for origin firm) and the first month on the new job (for the destination firm).

Figure 22: Mean Log Wages of Male Job Changers, by Quartile of Mean Wage at Origin and Destination Firm 2016-2018

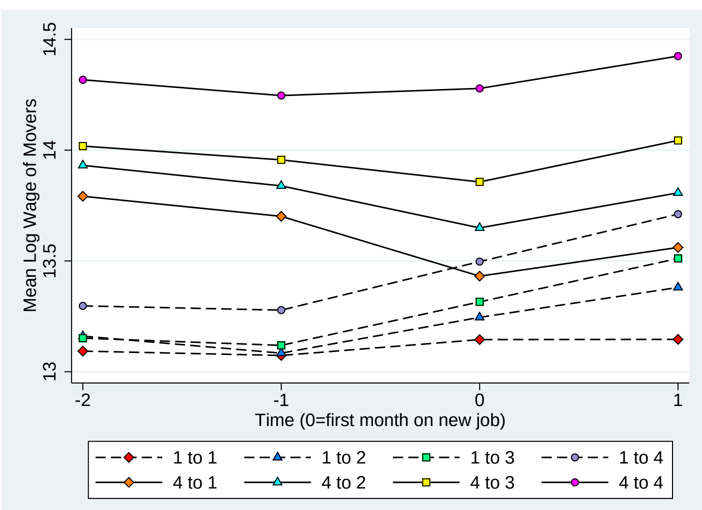
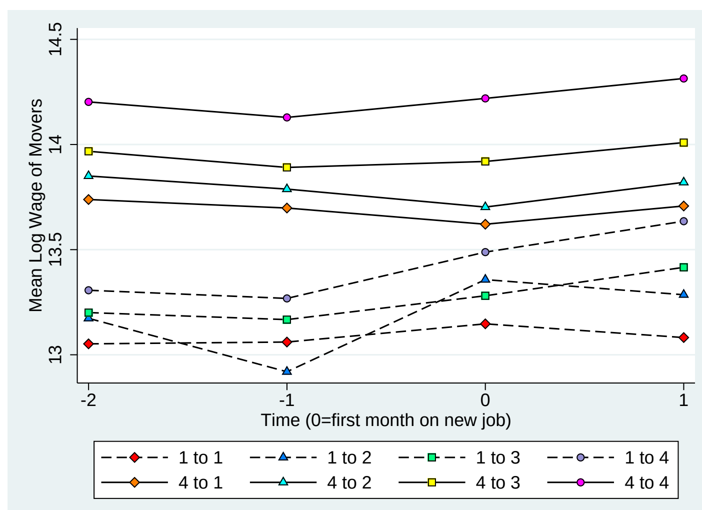


Figure 23: Mean Log Wages of Female Job Changers, by Quartile of Mean Wage at Origin and Destination Firm 2016-2018



Note: left (right) figure shows mean wages of male (female) workers at mixed-gender firms who changed jobs in 2016-2018 and held preceding job for 2 or more months, and new job for two or more months. Each job is classified into quartiles based on mean log wage of workers of both genders at the firm in the last month of the old job (for origin firm) and the first month on the new job (for the destination firm).

Figure 24: Mean Log Wages of Male Job Changers, by Quartile of Mean Wage at Origin and Destination Firm 2018-2020

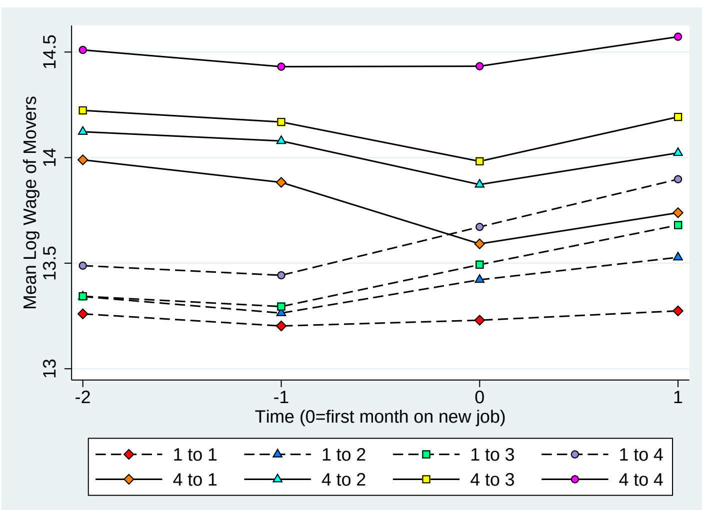
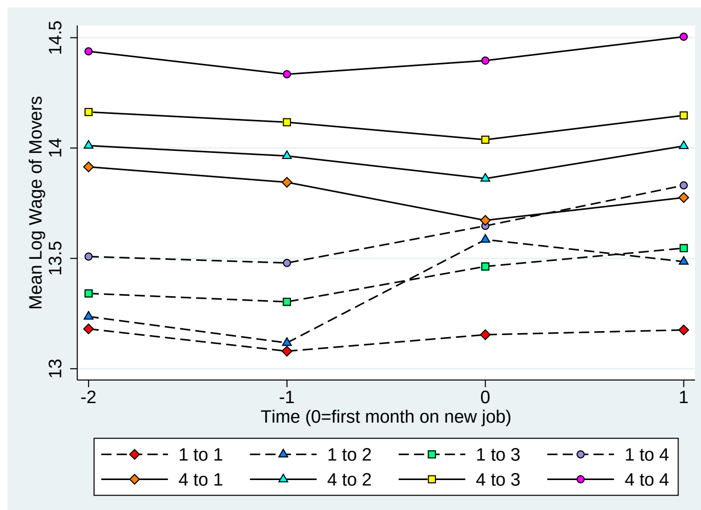


Figure 25: Mean Log Wages of Female Job Changers, by Quartile of Mean Wage at Origin and Destination Firm 2018-2020



Note: left (right) figure shows mean wages of male (female) workers at mixed-gender firms who changed jobs in 2018-2020 and held preceding job for 2 or more months, and new job for two or more months. Each job is classified into quartiles based on mean log wage of workers of both genders at the firm in the last month of the old job (for origin firm) and the first month on the new job (for the destination firm).