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Decomposing the Gender Wage Gap: The effects of Firm, Occupation and Job Stratification*

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Abstract

This paper presents new evidence on the role of segregation into firms, occupations within a firm and stratification into professional categories within firm-occupations in explaining the gender wage gap. I use a generalized earnings model that allows observed and unobserved group characteristics to have different impact on wages of men and women within the same group. The database is a large sample of individual wage data from the 1995 Spanish Wage Structure Survey.

Results indicate that firm segregation in our sample accounts for around one-fifth of the raw gender wage gap. Occupational segregation within firms accounts for about one-third of the raw wage gap, and stratification into different professional categories within firms and occupations explains another one-third of it. The remaining one-fifth of the overall gap arises from better outcomes of men relative to women within professional categories. It is also found that rewards to both observable and unobservable skills, particularly those related to education, are higher for males than for females within the same group. Finally, mean wages in occupations or job categories with a higher fraction of female co-workers are lower, but the negative impact of femaleness is higher for women.

1 Introduction

Even though the decline in gender wage differentials over the past two decades is a robust empirical regularity across almost all industrialized countries (see Altonji and Blank (1999) and Gosling and Lemieux (2001)), the presence of large and persistent wage differentials between male and female workers remains one of the most controversial features of modern labor economics. While some fraction of the earnings gap may be attributable to differences in observed skills, such as education, experience and job tenure, most of the gap seems to be related to males and females being segregated into different types of jobs. In particular, numerous previous studies accounted for female segregation into lower-paying occupations (Johnson and Solon (1986) and MacPherson and Hirsch (1995)). More recently, some authors have found evidence of female segregation into lower-paying firms (Carrington and Troske (1998)). Moreover, Bayard et al (2003) offers new evidence on sex segregation of females into lower-paying occupations within the same firm. In spite of the promising line of enquiry of the analysis of gender segregation within the same unit, the absence of large, representative samples that include information on individual workers' characteristics, as well as on firm and job characteristics, has limited the empirical evidence[1].

This paper presents new evidence on the role of segregation into firms, occupations within a firm and professional category within firm-occupations in explaining the gender wage gap, using a large sample of individual wage data from the 1995 Spanish Wage Structure Survey - known by its

[1] Abowd and Kramarz (1999) point out the importance of the use of matched worker-firm data sets in many areas of labor economics. At present, however, such data sets are scarce, and are often based on non-representative samples.

Spanish acronym as the EES[2]. The EES-95 collects data on the structure and amount of individual remuneration within a sample of establishments from the manufacturing, construction and service industries. For each selected establishment, there is individual information concerning wages, as well as other characteristics, such as education, job tenure and occupation from a random sample of workers. Given that information concerning the establishment which each worker belongs to is provided, there is complete information on a sample of co-workers of any worker in the sample. The EES, therefore, allows us to decompose the observed wage differential between males and females into components attributable to standard observed measures of skill, such as education, age (as a proxy for experience) and job tenure, to the distribution of men and women across different firms, to the distribution of men and women across different occupations within firms, and finally to the stratification of men and women into different professional categories within the same firm-occupation.

In order to perform such decomposition, I use a generalized earnings model that allows observed and unobserved group characteristics to have different effects on wages of men and women within the same group. This model nests the standard "group fixed effect" specification, a well as the "comparable worth" specification that has been used to explore the effect of occupational segregation on the gender wage gap (Johnson and Solon (1986)). Taking advantage of the detailed information available in the EES, and starting by considering the firm as the broadest group, I define two

[2]Salary structure surveys with the same structure as EES 95 exist in many EC countries, such as France, Germany and the United Kingdom, although in many countries statistical officers have not released the data to researchers.

more potential levels of grouping of workers within firms: the occupational level, and the professional category level within occupations. In Spain, jobs are stratified by their professional category level, which is defined by the base wage rate, available from the survey. Workers are stratified in different professional category levels even within occupations at the same firm.Workers belonging to the same professional category within an occupation at the same firm have the same base wage although their total wage may differ due to differences in wage complements.

Results indicate the following: The observed wage gap between men and women in the EES is 26 percent - comparable to the observed wage gap in 1991 for Spain (see De la Rica and Ugidos (1995)) - and to the wage gap observed in the mid-1990s in the U.K and the U.S (see Gosling and Lemieux (2001)). Around one-fifth of the overall gap is explained by the different distribution of men and women across firms. Within firms, differences in the distribution of men and women across occupations account for one-third of the overall gender gap, and a similar proportion is explained by differences in the distribution of males and females across professional categories within occupations. After controlling for professional category within firm-occupations, there is still a 4 percent gender wage gap. Thus, although segregation into different occupations within firms and segregation into professional categories within occupations (in the same firm) are important determinants of the gender wage gap in the Spanish labor market, about one-fifth of the overall gap arises from better outcomes of men within professional categories.

The analysis also suggests that in general, rewards to both observable and unobservable general skills, such as experience and education, are higher for males than for females within the same group. Regarding the latter, given the assumption that unobservable skills are correlated with average skills of the group, this implies that wages of workers assigned to groups with higher general skills have higher wages, and this effect is much stronger for men than for women. Finally, mean wages in occupations or job categories with a higher fraction of female co-workers are lower, but in contrast to the effect of mean education, the impact of femaleness is higher for women.

The rest of the paper is organized as follows: In section 2 some institutional features with respect to the wage setting process and wage composition in Spain are described. Section 3 describes the data. Section 4 presents the empirical specifications considered in the paper. Section 5 describes the results. Finally, section 6 concludes.

2 Institutional features

2.1 The wage setting process

Wages in Spain are determined by collective agreements, reached by employers' representatives and unions. These agreements include basically regulations about wage increases and hours of work for the period covered by the agreement (usually two years). Some important features of the wage setting process in Spain are the following: (i) The agreements are open-shop, i.e., they cover all workers, whether affiliated to unions or not[3].(ii) Collective agreements are carried out simultaneously at three levels

[3] This is at least part of the reason why union affiliation is less than 15% in Spain.

of aggregation, the industry collective agreement at the national level, the industry collective agreement at regional level (province) and finally, the firm level. The more aggregated levels are used as minimum benchmarks for more disaggregated levels. Around 88% of workers' wages are determined by collective agreements at regional level, whereas only around 15% of workers have a specific firm collective agreement. Collective agreements at firm level are usually signed only in big firms[4].

2.2 Wage Composition

Worker´s total ordinary wage is the sum of two components: (i) The base wage, and (ii) wage complements (shift-work, productivity, tenure, etc.). Each worker's base wage accounts for about 65 percent of her/his total ordinary wage. The base wage is linked to the professional category each worker is assigned to. Workers may belong to different professional categories within the same occupation. For instance, in an occupation such as office clerk (n^o 41 of ISCO-88), workers may be assigned to different professional categories, such as officer (of different degrees), supervisor, technician, assistant, etc. Promotion into a higher professional category entails an increase in the base wage. Ordinary wages of workers belonging to the same professional category within a particular occupation can only differ in the component of wage complements, not in the base wage.

[4]For a detailed description of collective agreements and wages in Spain, see Fina et al (2001).

3 The data

The data are taken from the Spanish Wage Structure Survey (EES 95), carried out in 1995. This survey collects data on the structure and amount of individual compensation within a sample of establishments from the manufacturing, construction and service industries. Its main advantage is that it collects individual and highly detailed information on different aspects of workers' wages, such as the base wage, extraordinary payments, other wage complements, etc, as well as some demographic and job characteristics of each worker. It is also much bigger than others currently existing in Spain[5]. Considering only full-time workers, the sample contains demographic and job characteristics of 125865 workers (99106 males and 26759 females) from 14347 different establishments. The sampling approach is a stratified two-stage sampling. In the first stage establishments, which are stratified by region (Autonomous Community) and size of firm (5 intervals), are selected randomly from the General Registry of Payments to Social Security. In the second stage, workers at each establishment are selected randomly. The survey is conducted at establishments with at least 10 workers. It is exhaustive in small units and for larger establishments a maximum of 25 workers per establishment are randomly interviewed. The code revealing the firm to which each worker belongs to is provided. Individual level information

[5]Unfortunately, individual information concerning wages in Spain is very scarce. The Spanish Labor Force Survey does not provide information on wages. Alternative information on individual wages for the nineties can only be found in the ECBC-1991 (Encuesta de Estructura, Conciencia y Biografía de Clase - for more details, see De la Rica and Ugidos (1995)) and the European Panel of Households (1994-2000). However, both are much smaller in size and no information concerning the establishment where workers work is available.

such as occupation, firm-specific seniority, education, age, hours schedule, days of absence from work and exhaustive information concerning wages is available.

To give an idea of how representative the sample is, workers at firms with ten or more employees accounted at that time for 70.75% (72,95% of males and 66,74% of females) of the total working population in Spain in 1995.

Table 1 presents descriptive statistics of the sample used for empirical analysis. Only men and women with full-time jobs are considered.

It can be seen that 73% of the sample are males, which is consistent with the gender distribution of full-time workers in 1995 in Spain, given that the gender distribution in Manufacturing, Construction and Services reported by the Spanish Institute of Statistics in the last term of 1995 (the time when the survey was carried out) for full-time workers is 70% and 30% for males and females, respectively. Table 1 presents the mean and standard deviation of the hourly ordinary wage, which is the wage variable used in the empirical part[6], as well as the hourly base wage [7]. It can be seen that in levels, the base wage accounts for 63% of total ordinary wage for males and of 70% for females. Furthermore, if we regress ordinary wage on the base wage, we find that only 37% of the variance in total wages is accounted for by variation in the base wage.

The raw ratio between female and male wages in this sample is 0.75, i.e., women workers earn on average 75 percent of the wages of male workers. This is very similar to the unrestricted gender wage ratio found using the ECBC-

[6] Results do not change significantly if ordinary plus overtime hourly wage is used instead.

[7] Both variables are measured in pesetas (1 peseta=1/166,386 euros)

91 for Spain - it was 0.74 - (see De la Rica and Ugidos (1995)). With respect to individual characteristics, it can be seen that males have on average more tenure, and are older and less educated. Finally, women are more likely to have temporary contracts than men.

[Insert table 1]

To give an idea of the sample gender segregation, table 2 presents the gender distribution of the sample by firm size (5 size intervals) and by broad occupational categories (one-digit ISCO-88). I also report the mean wage as well as the female-male wage ratio. From table 2, we can see that women are relatively more concentrated in big firms (though differences in the proportion of women are not very big) , which is where average gender wage differentials are higher, although mean wages are higher, too. Concerning the gender distribution among wide occupations, we can see that occupations such as clerks and service workers are the ones where women are more highly represented. These are precisely the ones where mean wages are lower.

[Insert table 2]

In order to assess the impact of the different aspects of gender segregation, three groups, or samples, have been considered. Before I describe each of them, I must say that each of the samples has been restricted to have at least one male and one female to properly account for gender wage differentials within groups. The broadest group considered is the firm to which workers belong. The sample consists of 8708 mixed gender firms. The second group is the worker's occupation within a firm. Occupations have been dissagregated at a two-digit level of ISCO-88. Given that this survey is directed at Manufacturing, Construction and Services firms, the database contains 65 different occupational categories[8]. This second sample consists of 6306 occupation-firm groups where there are both male and female full-time workers. Finally, the third group is defined by the professional category level each worker is assigned to within occupations and within firms. As mentioned before, in Spain jobs are stratified by the professional category level, which is defined by the base wage rate, available from the survey. The base wage for each professional category is determined by industry or firm collective agreements and workers are stratified in different professional category levels within occupations of the same firm. The third sample consists of 3610 mixed gender job category cells. As we move from the broadest group (firms) to the more restricted group (professional category), men and women belonging to the same group perform more similar tasks. Indeed, men and women working in the same professional category within an occupation in the same firm can be assumed to do "equal work". It can be assessed, therefore, whether men and women who do "equal work" receive "equal pay" or not. These groupings also allow us to measure how much of the gender wage gap is attributed to firm segregation, occupational segregation within firms and finally, to professional category segregation within occupations in the same firm.Table 3 presents some descriptive statistics of the final samples used to estimate wage differentials within each of the three groups. It can be seen

[8] In order to capture as much occupational gender segregation as possible, it is important to define detailed categories, inasmuch as the sample size allows for such a dissagregation.

that when we consider more restricted groups, the number of observations decreases notably, given that single gender cells (firms, occupations within firms, or job category) are not considered. It can also be noted that as we go into more detailed groups, men and women are more homogenous regarding observed skills.

[Insert table 3]

4 Empirical Specification

The general empirical specification begins with separate-by-gender standard relationships between the logarithm of hourly wages and individual human capital characteristics, observed job characteristics and an unobserved group effect

$$LnW_{imj} = \alpha_m + \beta_m X_{imj} + \gamma_m Z_{mj} + G_{mj} + \varepsilon_{imj} \qquad [1]$$
$$LnW_{ifj} = \alpha_f + \beta_f X_{ifj} + \gamma_f Z_{fj} + G_{fj} + \varepsilon_{ifj} \qquad [2]$$

where W_{imj} (W_{ifj}) is the (ordinary) hourly wage of the i^{th} male (female) of group j, X_{imj} (X_{ifj}) are individual measures of observed skills (age, tenure and education) of the i^{th} male (female) of group j, Z_{mj} (Z_{fj}) are job characteristics, such as occupation, industry and region of males (females) which are common to workers that belong to the same group, G_{mj} (G_{fj}) is the unobserved group effect for males (females) of group j, and ε_{imj} (ε_{ifj}) is the i^{th} male (female) specific error term component.

Assumptions about the nature of the unobserved group effect lead to different empirical specifications. In this paper, I present two empirical approaches: (i) the fixed effects model, which is a standard one, presented so as to compare it with other existing results, as well as with the other specification, and (ii) a more general earnings model, where the unobserved group effect is assumed to be random, correlated with the explanatory variables, and allowed to be different for males and females in the same group.

4.1 *Fixed effects model*

A very standard approach to estimate gender wage differentials is to assume that there is an unobserved fixed group effect which is common to all members within a group, and in particular, to males and females. Under this assumption, it is reasonable to write the "total group effect" (observed plus unobserved) as the sum of the Z variables previously described, which account for observed job characteristics, such as occupation, industry and region, common for every worker within a group, and the unobserved group effect:

$$\Phi_j = \gamma_m Z_{mj} + G_{mj} = \gamma_f Z_{fj} + G_{fj} \qquad [3]$$

We would then write equations [1] and [2] as:

$$LnW_{imj} = \alpha_m + \beta_m X_{imj} + \Phi_j + \varepsilon_{imj} \qquad [4]$$

$$LnW_{ifj} = \alpha_f + \beta_f X_{ifj} + \Phi_j + \varepsilon_{ifj} \qquad [5]$$

Equations [4] and [5] represent a very standard set of models of wage determination. In this case, log wages of males and females would be regressed on the $X's$ and $Z's$ of males and females, respectively, whereas the unobserved group effect, given the assumption that is fixed, would be captured by introducing group dummies as explanatory variables. This is a standard approach carried out by many studies that focus on gender wage differentials within groups, such as Bayard et al (2003), Barth and Mastekaasa (1996) and Groshen (1991).

The inexistence of an unobserved fixed effect can be seen as a particular case of this model. In such case, wage equations can be estimated by OLS without introducing group dummies, given that they would be zero under the assumption of inexistence of unobserved fixed effects[9].

Concerning average gender wage differentials between males and females under this framework, once the within-group parameters are consistently obtained from an OLS wage regression where group dummies are included as explanatory variables[10], we aggregate equations [4] and [5] up to the overall means in the following way:

$$W_{m/m} = \alpha_m + \beta_m X_{m/m} + \gamma Z + \Phi \qquad [6]$$

$$W_{f/f} = \alpha_f + \beta_f X_{f/f} + \gamma Z + \Phi \qquad [7]$$

where $W_{m/m}$ $(W_{f/f})$ are the weighted means of wages of males (females) across all groups, $X_{m/m}$ $(X_{f/f})$ are the weighted means of average skills of males and females across all groups and Z are average job characteristics, such as occupation, industry and region. The weights used are the proportion

[9]In the empirical part, separate OLS wage equations for males and females will also be reported for comparability reasons.

[10]Identical results concerning the within-group parameters $\alpha's$ and $\beta's$ would be obtained if instead of including group dummies, OLS estimation is applied to the variables demeaned from the group means.

of males (females) in each group, normalized by the mean proportion of males (females) in the sample. Given that the group effect is considered to be common to males and females, average gender wage differences can be written as the sum of differences in the intercept, $(\alpha_m - \alpha_f)$, and differences in average observable skills and in their rewards, $(\beta_m X_{m/m} - \beta_f X_{f/f})$.

4.2 *Random effects model*

A more general approach would be to consider the unobserved group effect to be random instead of fixed, which leads to the so called "random effects model". One non-restricted approach of such model is to allow for correlation between the explanatory variables and the unobserved group effect. Chamberlain (1982) studied this case and his approach was to replace the unobserved group effect with its linear projection onto the explanatory variables in all time periods plus the projection error. Ashenfelter and Zimmerman (1997) use this approach to estimate wage determination in the context of sibling data where individual wages of a pair of brothers depend on an unobserved random family effect that is correlated with the explanatory variables. For our particular case, where we have a cluster sample instead of a matched pairs sample, in order to specify the correlation of the group effect with the explanatory variables, we can linearly project the unobserved group effect onto the group-level average skills for males and females, respectively[11]. Furthermore, estimation of gender wage differentials commonly allows for differences in observable skills as well as in their rewards. However, measures

[11] This approach is very commonly used in the hierarchical models literature, where the unobserved effect is allowed to depend on cluster-level covariates, which is at the same time equivalent to adding cluster-level observables to the original model and relabeling the unobserved cluster effect.

of skills available in the data are far from perfect. Therefore, it is reasonable to expect gender wage differentials to be affected by differences in skills and in their rewards that are observed by the market but not by researchers. Hence, the most general approach to estimating a random effects model is to allow for correlation between the explanatory variables and the error term as well as for the existence of gender differences not only in the observable measures of skills, but also in the unobservable ones[12]. Finally, in many studies of gender wage differentials, it is suggested (see Johnson and Solon (1986), Bayard et al (2003)) that the group effect depends to a great extent on the "femaleness" of the group. In order to introduce this effect, the (sample) proportion of females in each group (F_j) can be introduced as an explanatory variable in the total group effect.

These premises lead us to specify G_{mj} and G_{fj} as:

$$G_{mj} = \lambda_{1m} X_{mj} + \lambda_{2m} \ X_{fj} + \delta_m F_j + \nu_{mj} \qquad [8]$$

$$G_{fj} = \lambda_{1f} X_{fj} + \lambda_{2f} \ X_{mj} + \delta_f F_j + \nu_{fj} \qquad [9]$$

Introducing G_{mj} and G_{fj} into equations [1] and [2] leads us to the following correlated random effects specification:

$$LnW_{imj} = \alpha_m + \beta_m X_{imj} + \gamma_m Z_{mj} + \lambda_{1m} X_{mj} + \lambda_{2m} X_{fj} + \delta_m F_j + \nu_{mj} + \varepsilon_{imj} \qquad [10]$$

$$LnW_{ifj} = \alpha_f + \beta_f X_{ifj} + \gamma_f Z_{fj} + \lambda_{1f} X_{fj} + \lambda_{2f} X_{mj} + \delta_f F_j + \nu_{fj} + \varepsilon_{ifj} \qquad [11]$$

[12] This approach is used in Lemieux (1998), where he specifies an unobserved firm effect of unionized workers on wages that is allowed to be different from that for non-unionized ones and no further restrictions are imposed.

where the composite errors are uncorrelated with the explanatory variables. Equations [10] and [11] are exactly identified and can be estimated by OLS. The $\lambda's$ would measure the impact of the average skill of the group co-workers for each worker's wages, whereas $\delta's$ would indicate the impact of the gender composition or femaleness of the group on individual wages.

Differences between the unobserved group effect for males and females within a group can be tested. In particular, if $\delta_m = \delta_f$ and $\lambda_{im} = \lambda_{if}$ $(i = 1, 2)$, we would conclude that within groups (firms, firm-occupation or professional category within occupations) unobserved skills are rewarded equally for both males and females.

This specification leads to a very general decomposition of the gender wage gap, given that gender wage differentials are being decomposed into differences in observed and unobserved skills, on the one hand, and differences in the rewards to the observed and unobserved skills, on the other. In order to capture these and the rest of the components determining mean gender wage differentials, we may proceed as follows:

a) Aggregate equations [10] and [11] by the group-by-gender level:

$$W_{mj} = \alpha_m + (\beta_m + \lambda_{1m})X_{mj} + \gamma_m Z_{mj} + \lambda_{2m}X_{fj} + \delta_m F_j \qquad [12]$$

$$W_{fj} = \alpha_f + (\beta_f + \lambda_{1f})X_{fj} + \gamma_f Z_{fj} + \lambda_{2f}X_{mj} + \delta_f F_j \qquad [13]$$

b) Aggregate [12] and [13] up to the overall gender means:

$$W_{m/m} = \alpha_m + (\beta_m + \lambda_{1m})X_{m/m} + \gamma_m Z_{m/m} + \lambda_{2m}X_{f/m} + \delta_m F \qquad [14]$$

$$W_{f/f} = \alpha_f + (\beta_f + \lambda_{1f})X_{f/f} + \gamma_f Z_{f/f} + \lambda_{2f}X_{m/f} + \delta_f F \qquad [15]$$

where, as before, $W_{m/m}$ $(W_{f/f})$ is the overall weighted means of male (female) wages, $X_{m/m}$ $(X_{f/f})$ and $Z_{m/m}$ $(Z_{f/f})$ are the weighted average observed skills of males (females) across all groups, and $X_{f/m}$ $(X_{m/f})$ are the weighted observed skills of females (males) across all groups. The weights used are, as before, the fraction of males (females) in the group, relative to the average proportion of males (females) in the sample.

Finally, subtracting [14] -[15] gives us the decomposition of the observed mean gender wage gap as a function of the following five components: (i) differences in the intercept, $(\alpha_m - \alpha_f)$, (ii) average differences in observed skills and their rewards between average males and females that work in "average" groups, $\{\beta_m X_{m/m} - \beta_f X_{f/f}\}$, (iii) average differences in observed job characteristics and their rewards between average males and females that work in "average" groups, $\{\gamma_m Z_{m/m} - \gamma_f Z_{f/f}\}$, (iv) average differences in unobserved skills and their rewards between males and females, $\{(\lambda_{1m} X_{m/m} + \lambda_{2m} X_{f/m}) - (\lambda_{1f} X_{f/f} + \lambda_{2f} X_{m/f})\}$, and (v) differences in the average impact of the "femaleness" of a group for males and females, $(\delta_m - \delta_f)F$.

5 Empirical findings

5.1 Fixed effect estimation

Table 4 presents the overall unadjusted gender wage gap for the whole sample, as well as the within groups unadjusted wage gaps. These raw gender wage gaps have been obtained from pool regressions (OLS and within-group estimations, respectively) of males and females on the female indicator. It is interesting to note that whereas the raw average gender wage gap of this sample is 0.25, it narrows considerably as different types of segregation are removed, or at least, greatly reduced[13]. In particular, the unadjusted gender wage gap narrows to 0.21 when we remove firm segregation, which means that on average, firm segregation in our sample accounts for around 19% of the unadjusted gender wage gap. Furthermore, when we remove occupational segregation within firms, the unadjusted wage gap narrows to 0.12, which means that occupational segregation within firms accounts for 33% of the raw wage gap. Finally, when we look at gender wage differences within professional categories within firm-occupation, the unadjusted wage gap decreases to 0.04, which means that different stratification into professional categories within firms and occupations accounts for 32% of the unadjusted wage gap. The remaining 16 percent is explained by better outcomes of men relative to women in the same job category.

[Insert table 4]

Table 5 presents OLS and fixed effect estimation for the three groups under consideration. The first important finding concerns differences in the rewards to observable skills for males and females. In all estimations, rewards to age and education are higher for males than for females, whereas the opposite is found with respect to tenure, whose rewards are invariably higher for females.

Comparing the results derived from the different within-group estimations, it is interesting to note that when we consider groups where

[13]If the assumption of fixed unobserved group effects is not correct, these group effects would not be completely removed by introducing group dummies as explanatory variables, but at least they would be reduced to a great extent.

workers accomplish more similar tasks, rewards to observable skills decrease, for both men and for women. This is particularly so for the rewards to age and education, whereas rewards to tenure seem to remain more stable. Moreover, in the within job category estimation, rewards to education for women become insignificantly different from zero. Given that among workers within the same job category only wage complements may differ (the base wage is the same for workers of the same job category within occupations of the same firm), this result suggests that differences in observed skills, particularly in education, do not seem to account much for differences in wage complements.

[Insert table 5]

Decomposition of weighted average gender wage differentials is presented in table 6. Following Oaxaca and Ransom (1994), non-discriminatory rewards have been considered as those obtained from a pool estimation of males and females. Differences in the rewards have been further decomposed into differences due to the advantage of males relative to the non-discriminatory rewards, and to the disadvantage of females relative to the non-discriminatory rewards[14]. Furthermore, in order to take into account that the discrimination components are not invariant to the "left out" reference group when there are dummies as explanatory variables, (see Oaxaca and Ransom (1999)), I have followed the approach suggested by Gardeazábal and Ugidos (2003), which is described in the appendix.

[14] This further decomposition has not been done for type of contract, industry and region, given its almost negligible total impact.

The numbers reported in table 6 are the relative contribution of each variable or group of variables to the average gender wage differential for each of the samples under consideration. Concerning OLS estimations, we can see that differences in observed skills, and more precisely, the disadvantage of females' rewards relative to the non-discriminatory ones, accounts for the biggest fraction of the observed average gender wage differential. Regarding wage decomposition within groups, the first thing to observe is that weighted average gender wage differences, i.e., average gender wage differences in "average groups", diminish when we consider mixed samples in more restricted groups. In the second place, we can observe that the impact of differences in characteristics in explaining the average gender wage differential decreases as we go from the mixed gender firm sample to the mixed gender job category sample. Moreover, in the latter sample, the impact of differences in characteristics is negligible, which is understandable, given that male and female workers present very similar observed characteristics.

Differences in the rewards to observable skills play a very important role, as in the OLS estimation, and as before, the disadvantage in the rewards for females relative to the non-discriminatory rewards seem to be clearly the factor which contributes most to explaining gender wage differences. It is true, though, that its relative importance decreases as we consider more restricted groups.

[Insert table 6]

5.2 Correlated random effects model

Estimations of equations [10] and [11] are presented in table 7. Panel A presents the results for males, and Panel B shows the results for females.

[Insert table 7]

The most important things to highlight are the following:

5.2.1 Rewards to observable skills:

Regarding rewards to observable skills, the $\beta's$, the first thing to observe is that those rewards relating to age and education diminish as we go from the mixed gender firms sample to the mixed gender job category sample. Moreover, for both males and females, rewards to education drop to zero for the mixed gender job category sample. As noted before, this indicates that differences in observed skills do not have a significant impact in explaining differences in wage complements between workers.

Comparing males and females, it can also be seen that such rewards are higher for males than for females (particularly, when we refer to general skills, such as age and education). This was also observed from the fixed effect estimation.

5.2.2 Rewards to unobservable skills:

Table 7 reveals that most $\lambda's$ are significantly different from zero. Moreover, when we go from the mixed gender firm sample to the mixed gender job category sample, some of these coefficients increase. In particular, an interesting result is that the average group level of education, particularly that of the males of the group, has a stronger positive impact on individual wages than the level of education of the individual himself/herself. One interpretation of this result, in line with the employer learning model developed by Altonji and Pierret (2001) and Farber and Gibbons (1996), would be that when hiring new workers, employers assign them to categories depending on observed measures of skills, such as experience and education. However, "good workers" will be promoted into higher categories as they reveal their ability to employers, whereas "bad workers" will not be promoted. After some time, high ability workers will be in the higher professional categories in the firm, whereas low ability workers will be in the lower ones. This would explain why it is the average level of education of the group, which reveals the group where the worker is assigned to depending on his/her ability, and not individual education per se, which has a higher impact on wages. The lack of longitudinal data prevents us from testing this interpretation more formally, given that it is not possible to see how rewards to observable and unobservable skills change as tenure in the firm increases.

5.2.3 Femaleness of the group:

We can see that the effect of the femaleness of a group on individual wages is negative and strong for males and for females for every group under consideration. The negative effect is significantly greater for females than for males.

These results lead us to conclude that (i) in general terms, rewards to observable and unobservable skills, particularly those concerning education, are higher for males than for females, and (ii) the more detailed the groups we consider are, the more impact rewards to unobservable skills have on wages.

5.2.4 Decomposition of the average gender wage gap

Table 8 presents the decomposition of the average gender wage gap from each of the samples under consideration. As in Table 5, relative contributions to the gap are reported for the different sets of variables under consideration. Furthermore, the total relative contribution is further decomposed into differences in characteristics and differences in rewards[15].

The first thing to note is that considering the total decomposition into differences in characteristics and differences in rewards, the impact of differences in characteristics does not decrease as we move from the mixed gender firm sample to the mixed gender job category sample, as we can see from the fixed effect estimation. The reason for that is that whereas the impact of differences in observed characteristics decreases, that of differences in unobserved skills increase. This means that a significant fraction of average gender wage differentials between males and females has to be found in the fact that unobservable skills play a more determinant role for the wages of males than for those of their female counterparts. An important advantage of the correlated random effect model over the fixed effects model, therefore, is that the former allows us to add another determinant for the gender wage gap, which is the impact of differences in unobserved skills on wage differentials.

We can also see that the impact of the femaleness of a group has to be taken into account when estimating wages. However, the femaleness of the

[15] As before, given that the relative contribution of variables, such as type of contract, occupation, industry and region is almost negligible, I have not decomposed that contribution further.

group does not seem to play a very important role on the explanation of gender wage differentials, unless we refer to the mixed gender job category sample.

[Insert table 8]

6 Conclusions

This paper presents new evidence on the role of segregation into firms, occupations within a firm and professional category within firm-occupations in explaining the gender wage gap. The method proposed is a a generalized earnings model that allows observed and unobserved group characteristics to have different effects on wages of men and women within the same group. This model nests the standard "group fixed effect" specification, a well as the "comparable worth" specification that has been used to explore the effect of occupational segregation on the gender wage gap.

The data are taken from a large sample of individual wage data from the 1995 Spanish Wage Structure Survey. This is a survey conducted at establishment level. Considering only full-time workers, the sample contains demographic and job characteristics on 125865 workers (99106 males and 26759 females) from 14347 different establishments.

Results indicate that firm segregation in our sample accounts for around one-fifth of the raw gender wage gap. Occupational segregation within firms accounts for about one-third of the raw wage gap, about the same as stratification into different professional categories within firms and occupations. The remaining one-fifth of the overall gap arises from differences in outcomes within professional categories.

The analysis also suggests that rewards to both observable and unobservable skills, particularly those related to education, are higher for males than for females within the same group. Given the assumption that unobservable skills are correlated with average skills of the group, this implies that workers assigned to groups with higher education have higher wages, and this effect is much stronger for men than for women. Finally, mean wages in occupations or job categories with a higher fraction of female co-workers are lower, but in contrast to the effect of mean education, the negative impact of femaleness is higher for women.

Appendix: Identification of all dummy variables in the Wage Decomposition.

As Gardeazábal and Ugidos (2003) show, the contribution to discrimination of each individual dummy variable can be easily identified through the introduction of the following identification restriction[16]:

$$\sum_{j=1}^{J} \beta_j = 0$$

where $j = 1, ..J$ are the J categories of a particular dummy variable, such as occupation, type of contract, industry or others.

[16] This restriction is typically introduced in ANOVA analysis.

Assuming, for the sake of simplicity, that there is only one explanatory variable, which is a dummy with J different categories, estimation of the wage equation subject to this identification restriction amounts to estimating the following wage equation:

$$LogW_i = \alpha + \sum_{j=2}^{J} \beta_j (D_j - D_1) + u_i$$

where D_1 is the dummy of the left out reference group.

The parameters can be easily estimated by OLS on this transformed equation, and the coefficient of the omitted category is given by $\widehat{\beta_1} = -\sum_{j=2}^{J} \beta_j$. Therefore, $\widehat{\beta_1}$ is also identified, and hence the contribution of the reference category of each of the dummy variables can be incorporated into the average wage decomposition.

Once all the $\beta_j's$ are obtained for males, females and from the pool sample, $\widehat{\beta_{jm}}, \widehat{\beta_{jf}}, \widehat{\beta_{jp}}$, the estimated wage decomposition, considering that the non-discriminatory rewards are those obtained from the pooled regression, would be the following:

$\overline{W_{m/m}} - \overline{W_{f/f}} = (\widehat{\alpha_m} - \widehat{\alpha_f}) + \sum_{j=1}^{J} \widehat{\beta_{jp}}(\overline{D_{jm/m}} - \overline{D_{jf/f}}) + \sum_{j=1}^{J}(\widehat{\beta_{jm}} - \widehat{\beta_{jp}})\overline{D_{jm/m}} + \sum_{j=1}^{J}(\widehat{\beta_{jp}} - \widehat{\beta_{jf}})\overline{D_{jf/f}}$

References

[1] Abowd, J. and F. Kramarz (1999), "The analysis of labor markets using matched employer-employee data", Handbook of Labor Economics, vol. 3B (chapter 40) ,ed. Ashenfelter and Card, Elsevier Science.

[2] Altonji, J. and R. Blank, (1999), "Race and Gender in the Labor Market", Handbook of Labor Economics, vol. 3C (chapter 48) ,ed. Ashenfelter and Card, Elsevier Science.

[3] Altonji, J. and C. Pierret (2001), "Employer Learning and Statistical Discrimination", *Quarterly Journal of Economics, vol. 116.*

[4] Ashenfelter, O. and D. Zimmerman, (1997), "Estimates of the returns to schooling from sibling data: Fathers, sons and brothers", *The Review of Economics and Statistics, vol. LXXIX, N. 1.*

[5] Barth, E. and A. Mastekaasa (1996), "Decomposing the Male/Female wage gap: Within and between Establishment differences", *Labour, 10 (2).*

[6] Bayard, K., J. Hellerstein, D. Neumark and K. Troske (2003): "New evidence on sex segregation and sex differences in wages from matched employee-employer data", *Journal of Labor Economics, vol. 21(4), pp.887-923.*

[7] Carrington, W. and K. Troske (1998), "In measuring segregation in samples with small units", *Journal of Business and Economic Statistics, vol. 15(4).*

[8] De la Rica, S. and A. Ugidos (1995), "¿Son las diferencias salariales en capital humano determinantes de las diferencias salariales observadas entre hombres y mujeres? ", *Investigaciones Económicas, vol.XIX, pp. 395-414.*

[9] Chamberlain, G. (1982), "Multivariate regression models for panel data", *Journal of Econometrics 18(5).*

[10] Farber, H. and R. Gibbons (1996), "Learning and Wage dynamics", *Quarterly Journal of Economics, vol. 111.*

[11] Fina, L., F. Gonzalez and J.I. Perez Infante (2001), "Negociación Colectiva y Salarios en España", Colección Estudios (110), Consejo Económico y Social.

[12] Gardeazábal, J. and A. Ugidos (2003), "More on Identification in detailed wage decompositions", WP2002-17, Departamento de Fundamentos del Análisis Económico, Universidad del País Vasco.

[13] Gosling, A. and T. Lemieux (2001), "Labour market reforms and changes in wage inequality in the United Kingdom and the United States", *NBER Working Paper Nº 8413.*

[14] Groshen, E. (1991), "The Structure of the Female/Male Wage differential: Is it who you are, what you do, or where you work?" *The Journal of Human Resources, vol. 26 (3).*

[15] Johnson, G. and G. Solon, (1986), "Estimates of the Direct Effects of Comparable Worth Policy", *American Economic Review, 76 (5), 1117-25.*

[16] Lemieux, T. (1998), ""Estimating the effects of Unions on Wage Inequality in a Panel Data Model with Comparative Advantage and Nonrandom selection", *Journal of Labor Economics, 16 (2).*

[17] MacPherson, D. and B. Hirsch (1995), "Wages and Gender Composition: Why do womens's Jobs Pay less?" *Journal of Labor Economics, 13(4).*

[18] Oaxaca, R . and M.R. Ransom (1994), "On discrimination and the decomposition of wage differentials", *Journal of Econometrics, vol. 61, pp.5-21.*

[19] Oaxaca, R . and M.R. Ransom (1999), "Identification in detailed wage decompositions", The Review of *Economics and Statistics, vol. 81 (1), pp. 154-157.*

Table 1: Descriptive Statistics of the Sample						
Variables	**All**		**Males**		**Females**	
	Mean	St. dev.	Mean	St. dev.	Means	St. dev.
Hourly ordinary wage	1030.7	667.9	1089.0	706.7	814.7	434.9
Hourly base wage	672.2	430.8	692.2	457.5	598.2	301.2
Age	38.71	10.88	39.79	9.70	34.73	9.70
Tenure	10.89	9.98	11.36	10.18	9.14	8.95
Years of education	8.65	3.86	8.50	3.89	9.22	3.71
% Temporary contract	0.25	-	0.23	-	0.28	
N. of observations	125865		99106		26759	

Table 2: Gender distribution across firms and wide occupations				
	N.observations	**%Female**	**MeanWage***	$\frac{FemWage}{MaleWage}$
Firm Size				
10-19 workers	24847	18.8	822.6	0.79
20-49 workers	32378	19.3	908.4	0.75
50-99 workers	21176	21.9	1018.2	0.72
100-199 workers	19187	22.8	1111,5	0.71
>199 workers	28277	24.0	1308.2	0.70
Wide Occupations				
White-Collar occupations				
Managers	5152	7.1	2366.3	0.72
Professionals	5711	18.2	1813.0	0.77
Technicians & ass.prof.	13243	20.1	1387.0	0.81
Clerks	17455	47.6	977.2	0.77
Service Workers	7823	35.1	744.8	0.80
Blue-Collar Occupations				
Craft workers	27771	10.4	902.1	0.71
Plant and machine oper.	34260	15.7	900.3	0.73

* The wage variable is hourly ordinary wage, it is measured in pesetas (1peseta=1/166.386 euros) . This is the variable used in the empirical analysis.

Table 3: Descriptive Statistics of the samples of mixed gender groups				
Variables	**Males**		**Females**	
Panel A: Sample of mixed gender firms (N = 8708 firms)				
	Mean	St. dev .	Mean	St. dev
Log hourly ordinary wage	6.91	0.52	6.60	0.44
Age	39.64	10.91	34.84	9.81
Tenure	11.84	10.27	8.99	8.91
Years of education	9.01	4.02	9.24	3.72
Managers and technicians	0.18	0.39	0.13	0.34
Clerks	0.11	0.30	0.32	0.47
Service workers	0.06	0.24	0.10	0.31
Craft workers	0.47	0.49	0.27	0.44
Machine operators	0.10	0.30	0.15	0.35
N. of observations	62462		24770	
Panel B: Sample of mixed gender occupation-firm (N= 6306 cells)				
Log hourly ordinary wage	6.84	0.50	6.62	0.45
Age	37.78	10.74	34.65	9.62
Tenure	11.34	10.24	9.30	9.15
Years of education	9.14	3.88	8.96	3.69
Managers and technicians	0.18	0.38	0.13	0.34
Clerks	0.20	0.39	0.21	0.40
Service Workers	0.13	0.33	0.14	0.35
Craft workers	0.39	0.48	0.38	0.48
Machine operators	0.10	0.27	0.14	0.31
N. observations	17457		14099	
Panel C: Sample of mixed gender Job categories (N = 3610 cells)				
Log hourly ordinary wage	6.73	0.45	6.61	0.42
Age	35.83	10.52	33.95	9.40
Tenure	9.51	9.62	8.52	8.93
Years of education	9.01	0.46	9.02	3.64
Managers and technicians	0.13	0.34	0.11	0.32
Clerks	0.21	0.41	0.21	0.41
Service workers	0.14	0.35	0.15	0.35
Craft workers	0.37	0.48	0.37	0.48
Machine operators	0.15	0.33	0.16	0.34
N. observations	7122		6539	

Table 4: Unadjusted Gender Wage Gap				
OLS and Within-group Wage Reg. - Pooled sample				
Dep.Variable: Log Hourly ordinary Wage				
	OLS	**W-F**	**W-OF**	**W-JC**
Female	-0.258	-0.210	-0.121	-0.04
	(0.0003)	(0.003)	(0.003)	(0.003)

W-F: Within-Firm estimation; W-OF: Within Occupation-Firm estimation;

W-JC: Within Job Category estimation

Table 5: OLS and Fixed effect estimation of Log wages				
Panel A: MALES				
Variables	OLS^{+}	W-F *	W-OF*	W-JC*
Age	0.046	0.041	0.028	0.008
	(0.0008)	(0.0009)	(0.001)	(0.002)
Age^2	-0.0004	-0.0003	-0.0003	-0.7*e^{-4}
	(0.9*e^{-5})	(0.1*e^{-4})	(0.1*e^{-3})	(0.2*e^{-4})
Tenure	0.010	0.007	0.008	0.009
	(0.0005	(0.0005)	(0.001)	(0.001)
Tenure^2	-0.5*e^{-4}	-0.3*e^{-3}	-0.4*e^{-3}	-0.7*e^{-4}
	(0.1*e^{-4})	(0.1*e^{-3})	(0.2*e^{-4})	(0.3*e^{-4})
Education	0.041	0.040	0.013	0.002
	(0.0003)	(0.0004)	(0.0008)	(0.001)
(TC-PC)$^{+}$	-0.125	-0.15	-0.102	-0.035
	(0.004)	(0.004)	(0.008)	(0.009)
Intercept	5.38	5.60	5.74	6.47
	(0.017)	(0.018)	(0.048)	(0.04)
N. observ.	99106	62462	17457	7122
PANEL B: FEMALES				
Age	0.035	0.022	0.013	0.004
	(0.001)	(0.0012)	(0.002)	(0.002)
Age^2	-0.0003	-0.0002	-0.0001	-0.3*e^{-4}
	(0.1*e^{-4})	(0.1*e^{-4})	(0.2*e^{-3})	(0.2*e^{-4})
Tenure	0.012	0.012	0.014	0.009
	(0.0009)	(0.0009)	(0.001)	(0.001)
Tenure^2	-0.2*e^{-4}	-0.0001	-0.0002	-0.0001
	(0.2*e^{-4})	(0.2*e^{-3})	(0.3*e^{-3})	(0.3*e^{-4})
Education	0.031	0.024	0.007	0.001
	(0.0006)	(0.0007)	(0.001)	(0.001)
(TC-PC)$^{++}$	-0.077	-0.084	-0.05	-0.02
	(0.006)	(0.006)	(0.008)	(0.008)
Intercept	5.41	5.80	6.18	6.46
	(0.027)	(0.025)	(0.033)	(0.031)
N. observations	26759	24770	14099	6539

*W-F: Within Firm estimation; W-OF: Within Occupation-firm estimation;

W-JC: Within Job category estimation.

$^{+}$ OLS estimation also includes four dummies for occupation, 8 dummies for industry

and 16 dummies for region. The Within-firm estimation also includes four dummies for occupation.

$^{++}$(TC-PC)= (Temporary Contract - Permanent Contract). See appendix for details concerning

how dummies have been included for identification in the decomposition of wage diff.

Table 6: Decomposition of average wage gap				
OLS and Fixed effects estimation				
Relative contribution to the Wage Gap				
	All	Sample 1°	Sample 2°	Sample 3°
$(W_{m/m} - W_{f/f})^*$	0.26	0.27	0.18	0.09
	OLS	*Within-group estimations*		
		W-F	W- OF	W-JC
$\beta_*(X_{m/m} - X_{f/f})$	0.27	0.31	0.15	0.05
$X_{f/f}*(\beta_* - \beta_f)$	0.54	0.46	0.47	0.50
$X_{m/m}*(\beta_m - \beta_*)$	0.29	0.23	0.38	0.45
Human Capital				
Total	1.25	1.93	2.00	1.00
$\beta_*(X_{m/m} - X_{f/f})$	0.20	0.19	0.16	0.05
$X_{f/f}*(\beta_* - \beta_f)$	1.08	1.34	1.24	0.60
$X_{m/m}*(\beta_m - \beta_*)$	-0.03	0.40	0.60	0.35
Type of contract- Total	0.09	0.06	0.05	0.03
Ocupation - Total	-0.02	-0.05	—	–
Industry - Total	0.11	—	—	—
Region - Total	-0.01	—	—	—
Intercept	-0.42	-0.94	-1.05	-0.03

°Sample 1: Mixed gender firms; Sample 2: Mixed gender occupation-firm;

Sample 3: Mixed gender Job Category.

* In column [1], $(W_{m/m} - W_{f/f})$ is the raw mean difference of wages.

+ The impact of type of contract, industry and region have not been dissagregated further given their almost negligible impact relative to the other set of variables.

Table 7: Correlated random effect model for wages*									
Panel A: MALES									
	M.G Firms			**M.G Occup-Firm**			**M.G. Job Cat.**		
	β_m	λ_{1m}	λ_{2m}	β_m	λ_{1m}	λ_{2m}	β_m	λ_{1m}	λ_{2m}
Age	0.043	0.002	0.001	0.035	0.005	0.002	0.016	0.005	0.003
	(0.0013)	(0.0008)	(0.0005)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
Age^2	-0.0004	—	—	-0.0004	—	—	-0.1*e^{-3}	—	—
	(0.1*e^{-3})			(0.3*e^{-4})			(0.3*e^{-4})		
Tenure	0.008	0.003	0.001	0.009	0.002	0.9*e^{-4}	0.010	0.002	0.003
	(0.0009)	(0.0008)	(0.0006)	(0.001)	(0.001)	(0.9*e^{-3})	(0.002)	(0.002)	(0.001)
Ten^2	-0.6*e^{-4}	—		-0.8*e^{-4}	—	—	-0.1*e^{-3}	—	—
	(0.2*e^{-4})			(0.4*e^{-4})			(0.6*e^{-4})		
Educ.	0.037	0.011	0.006	0.013	0.021	0.014	0.001	0.021	0.019
	(0.0007)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
P.Fem.	-0.153	—	—	-0.152	—	—	-0.13	—	—
	(0.019)			(0.026)			(0.036)		
Interc.	5.09	—	—	5.19	—	—	5.59	—	—
	(0.043)			(0.065)			(0.075)		
N. obs.		62462			17457			7122	
PANEL B: FEMALES									
	β_f	λ_{1f}	λ_{2f}	β_f	λ_{1f}	λ_{2f}	β_f	λ_{1f}	λ_{2f}
Age	0.029	0.002	-0.0005	0.023	0.005	0.001	0.014	0.005	0.003
	(0.002)	(0.0007)	(0.0007)	(0.002)	(0.0009)	(0.0009)	(0.003)	(0.001)	(0.001)
Age^2	-0.0003	—	—	-0.2*e^{-3}			-0.1*e^{-3}	—	—
	(0.2*e^{-4})			(0.3*e^{-4})			(0.5*e^{-4})		
Tenure	0.009	0.002	0.003	0.011	0.0009	0.002	0.007	0.005	0.003
	(0.001)	(0.0008)	(0.0007)	(0.001)	(0.0008)	(0.001)	(0.002)	(0.001)	(0.001)
Ten^2	-0.4*e^{-4}	—	—	-0.8*e^{-4}			-0.9*e^{-4}	—	—
	(0.3*e^{-4})			(0.5*e^{-4})			(0.7*e^{-4})		
Educ.	0.020	0.004	0.015	0.007	0.025	0.008	0.001	0.025	0.011
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)
P.Fem.	-0.226	—	—	-0.210			-0.203	—	—
	(0.018)			(0.025)			(0.034)		
Interc.	5.504	—	—	5.49	—	—	5.69	—	—
	(0.047)			(0.061)			(0.078)		
N. obs.		27648			14099			6539	

* Covariates also include a dummy for type of contract, 4 dummies for occupation,

17 region dummies and 4 dummies for industry.

Robust standard errors in brackets.

Table 8: Decomposition of the average gender wage gap			
Corrrelated Random Effects Estimation			
Relative Contribution to the gap			
	Sample 1°	Sample 2	Sample 3
$(W_{m/m} - W_{f/f})$	0.27	0.18	0.09
Total			
$\beta_*(X_{m/m} - X_{f/f})$	0.60	0.55	0.54
$X_{f/f}*(\beta_* - \beta_f)$	0.27	0.22	0.22
$X_{m/m}*(\beta_m - \beta_*)$	0.13	0.23	0.24
Differences in Human Capital			
Total	2.12	2.08	0.91
$\beta_*(X_{m/m} - X_{f/f})$	0.13	0.16	0.05
$X_{f/f}*(\beta_* - \beta_f)$	1.47	1.39	0.95
$X_{m/m}*(\beta_m - \beta_*)$	0.52	0.53	-0.09
Type of Contract - Total	0.07	0.02	0.07
Occupation - Total	-0.01	0.01	0.04
Industry - Total	0.06	0.08	-0.003
Region - Total	0.03	0.05	0.15
Differences in the unobserved group effects			
Total	0.04	0.03	0.36
$\lambda_*(X_{m/m} - X_{f/f})$	0.03	0.08	0.14
$X_{f/f}*(\lambda_* - \lambda_f)$	-0.28	-0.66	-0.66
$X_{m/m}*(\lambda_m - \lambda_*)$	0.29	0.61	0.88
Femaleness of a group	0.26	0.29	0.59
Differences in the Intercept	-1.57	-1.53	-1.11

°Sample 1: Mixed gender firms; Sample 2: Mixed gender occupation-firm;

Sample 3: Mixed gender Job Category.