The Effects of Gender Segregation at the Establishment Level on Wages: An Empirical Analysis Using a Panel of Matched Employer-Employee Data

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Abstract

This paper studies the relationship between segregation of women across establishments and the wages of males and females. To investigate this issue empirically we use a panel of matched employer-employee data from Brazil. Various longitudinal models are used to assess the wage impact of establishment gender segregation. Overall, the results indicate that the effect of establishment female proportion on the wages of males and females is negative. We also compare these longitudinal results with cross-section estimates, which are the usual ones obtained in the related literature. This comparison suggests that unmeasured, time-invariant worker- and establishment-specific effects are correlated with the establishment female composition.

1 Introduction

The existence of gender differences in wages is a phenomenon that has been documented by many scholars for several different countries and periods of time. One of the main findings of this research is that there is a connection between the wages of men and women and the gender composition of occupations, industries, and firms. Such evidence has been important not only to improve our understanding about the channels through which gender pay differentials occur, but also to assess the effectiveness of the various policies that aspire to reduce the gender wage gap.

Most of the literature has focused on the relationship between wages and gender composition at the occupational and industry levels.[1] One of the established empirical findings of these studies is that workers' wages vary systematically with the gender composition of

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[1]Among the many international studies that examine the relationship between sex segregation and wages at the occupation and industry levels are Bergmann (1974), Polachek (1979), Treiman and Hartmann (1981), Blau (1984), Johnson and Solon (1986), Sorensen (1989), Filer (1989), Killingsworth (1990), Blau and Ferber (1992), England (1992), Macpherson and Hirsch (1995), Fields and Wolff (1995). There are a few Brazilian studies that examined this issue, e.g. Barros et al. (1997), Ometto et al. (1997), Ometto et al. (1999), and Oliveira (2001).

occupations and industries. Specifically, the empirical evidence shows that the proportion of females in occupations and industries is negatively related to the wages of males and females.

Less attention has been given to the connection between wages and sex segregation at the firm level.[2] The first studies that used cross-employer information (McNulty, 1967; Buckley, 1971; Blau, 1977) found that women were segregated into lower paying employers, a finding that has been consistently reproduced in more recent studies (Groshen, 1991; Carrington and Troske, 1995, 1998; Bayard et al., 1999; Reilly and Wirjanto, 1999a; Vieira et al., 2003). The results from these studies show that the relationship between the gender composition of establishments and the wages of males and females is negative.[3]

However, all these cross-employer studies are based on cross-section data. This may be seen as a limitation, since this type of data does not allow econometric specifications that include unobserved worker- and firm-specific effects that may potentially influence the wage level of males and females, and be correlated with explanatory variables in the model. More specifically, to the extent that unobserved worker-specific traits (such as ability, motivation, and preferences) and firm-specific characteristics (such as employers' efficiency and discriminatory tastes) affect the wage levels of the two sex groups and are correlated with other covariates in the model (e.g. the gender composition of firms), parameter estimates based cross-section data are deemed to be misleading.

One of the main contributions of the this paper is the estimation of longitudinal models that control for those unobserved specific effects in measuring the relationship between the gender composition of establishments and wages. Another advantage of using longitudinal methods is that they allow the estimation of more general models that allow different assumptions about the structure of the disturbance term (e.g. autoregressive models). To the best of our knowledge, this is the first study that investigates the relationship between gender segregation at the employer level and individual wages using a panel with information on both employers and workers.[4]

To conduct longitudinal-type estimation we use a panel of matched employer-employee data based on administrative files maintained by the federal government in Brazil. The data set is rich in that it contains information on important productive-related characteristics of the workers (e.g. schooling and tenure) and also relevant information on the employers (e.g. employment size and industry). In addition, the number of observations available in the data set is very large, making it possible to obtain more reliable estimates of the parameters of interest. Methodologically we use dynamic panel data methods. We also implement various other methods to check the robustness of the results. As a preview, our results indicate that the effect of gender segregation at the establishment level is negative on the wages of males and females. The comparison with estimates from cross-section regressions shows a reduction of this effect (i.e. it becomes less negative) for both sex groups, suggesting that the cross-section estimates may be biased downwards.

[2]This is probably due to the lack of public, comprehensive micro-data with information on both the employers and employees. Indeed, the availability of nation-wide linked employer-employee data in the last decade has allowed the appearance of many studies at the firm level, including those that focused on the issue of gender differentials. For a survey of linked employer-employee data sets and the econometric issues associated with them, see e.g. Abowd and Kramarz (1999).

[3]There is no Brazilian study that investigated this relationship at the employer level.

[4]Abowd et al. (1999) use a panel of linked employer-employee data to estimate the effects of typical human capital variables on the wages of males and females, but they do not include any measure of gender segregation at the employer level. Macpherson and Hirsch (1995) use longitudinal data to investigate the effect of occupational gender segregation on wages, but they use household surveys with no information at the employer level.

There are several theories of the male-female wage gap that are based on sex segregation at the firm level. For instance, Becker (1971) and Arrow (1973a,b) predict that the existence of discriminatory tastes by employers, employees, or customers may lead to sex segregation at the firm level and the appearance of a gender wage differential. Another theory is the statistical discrimination model, which is based on the idea that employers have imperfect information about the true productivity of individual workers and form beliefs that, on average, females are less productive than males. There is also the so-called quality-sorting hypothesis, whose main assumptions are that skill requirements vary across employers and that men and women have different skills, with the latter being less qualified. Reilly and Wirjanto (1999b) propose a theory based on what they call "coincidence of needs" between employers and workers that may also generate sex segregation and pay differences between males and females.

Though we do not attempt to look for evidence that favours any of these theories, we develop two models whose predictions may be compatible with our empirical results and the available evidence on the connection between gender segregation at the establishment level and the wages of males and females. In the first model we embed Becker/Arrow model of employer discrimination in a monopsonistic framework.[5] In the second model we combine the theory of statistical discrimination and the quality-sorting hypothesis to build-up a framework, which, we believe, is the first attempt to formally put these two theories together.

The analysis of this paper is also motivated by policy concerns. Many of the policies that have been proposed to reduce the gender pay gap are based on the idea that the wages paid to workers in jobs of similar value (e.g. same skill requirements, responsibility, and working conditions) should be equal. For instance, the main goal of comparable worth provisions is to equalise the wages of occupations that are typically held by women to wages of occupations of comparable worth that are typically held by men.[6] Another type of policy aims at giving equal employment opportunities to women in the labour market. This type of policy tries to deal directly with the issue of female segregation at the firm level, and in this sense differs from comparable worth initiatives.

This paper is structured as follows. In section 2 we present a brief review of the empirical literature that investigated the relationship between establishment gender segregation and wages. Section 3 is dedicated to review the theories that aim to explain the relationship between sex segregation and wages of females and males. We also include in this section two different stylised models of sex segregation and wages at the firm level. Section 4 describes the data set we use for estimation and provides descriptive statistics on its main characteristics. In section 5 we measure the degree of sex segregation across establishments. Since part of the interplant segregation we observe may be the result of random allocation of workers across establishments, we follow Carrington and Troske (1997) in computing their measures of random and systematic segregation. Section 6 describes the empirical methodology we employ to estimate the relationship between sex segregation and individual wages, and the corresponding results are presented in section 7. In section 8 we conduct various robustness checks. Section 9 is a discussion section in which we summarise

[5] Becker/Arrow model is a competitive model in which all firms pay the same equilibrium wage. By embedding it in a monopsonistic framework, our model allows the appearance heterogeneous wages across firms.

[6] The implementation of this type of policy are usually done on a employer-by-employer basis, meaning that discrepancies *within* firms are dealt with, while disparities *across* firms are not. Thus, if there is sex segregation at the workplace with women holding jobs at lower paying firms, the effectiveness of such policies are reduced. This was the point made by Johnson and Solon (1986).

our results, compare them with cross-section estimates (both ours and those of previous research), and obtain gender wage gap decomposition results, which are used to discuss some policy implications. Conclusions are presented in section 10.

2 Related Empirical Literature

In this section we summarize the results from previous empirical studies that have investigated the relationship between establishment gender segregation and the wages of workers. To follow more concretely this review, Table 1 presents some of the main features of these studies. The last column of this Table contains a summary of the empirical findings for the relationship of interest. We have only included studies that have used establishment-level data.

McNulty (1967) and Buckley (1971) were the first to show that interfirm gender segregation was an important factor determining the gender wage gap. Using unpublished data they show that women tended to work in low-paying firms, while men in high-wage ones. For instance, McNulty (1967) found that firms with only male janitors paid wages that were 37% higher than the wages paid by firms that only employed female janitors. In contrast, men's wages were only 18% higher in firms that employed janitors of both sexes. Similarly, Buckley (1971) shows that the unweighted average of the male-female wage ratios across occupations in single-sex firms was 1.22, while the corresponding figure for integrated firms was 1.11. Blau (1977) generalised these results by computing the correlation between the ranking of firms in terms of wages with the ranking of the same firms in terms of their female proportion. These rankings were obtained from the coefficients associated with firm dummies in two separate regressions, one where the dependent variable was the wage of workers, and another where the dependent variable was the proportion of females of firms. The estimated correlation coefficient was negative for the three statistical metropolitan areas used in the study, a result that shows that the higher the (mean) wage paid by the firm, the lower the proportion of females in its workforce.

Groshen (1991) studied five specific industries and found that the relationship between establishment gender segregation and wages was negative in all industries. For some industries she also found that sex segregation at the firm level was one of the most important factors determining the gender gap in wages. In other industries the occupational segregation component played a major role. Her study, however, does not include typical productive-related characteristics of workers and firms, which are, presumably, important controls in gender wage regressions.

Using a sample of small firms, Carrington and Troske (1995) run a regression at the firm-level in which the average (per employee) payroll of firms is regressed against a set of firms' controls and a categorical variable measuring the proportion of females in the firm. Their results show that firms that have a predominantly male workforce tend to pay higher average wages than firms with predominantly female employees. Carrington and Troske (1998) use a sample of manufacturing plants that were linked to the U.S. 2000 Census information so as to have a matched employer-employee data set. Including controls for workers' and establishments' characteristics, they regress individual wages on a female dummy, a (continuous) establishment female proportion variable, and the interaction between these two variables. This interaction term allows them to capture the effect of establishment sex segregation on males' and females' wages. Their results show that this effect is negative for both sexes, being stronger (i.e. more negative) for females.

Bayard et al. (1999) use a similar data set as in Carrington and Troske (1998). Differ-

ently from Groshen (1991) they include a large set of controls for workers' and establishments' characteristics in their regressions, but also found that establishment gender segregation is an important component in the male-female wage gap. From their regressions estimated by sex, the estimated establishment female proportion coefficient is negative for both sexes, being again more negative for females.

Reilly and Wirjanto (1999a) use a small sample of matched employer-employee data from Canada and run Generalised Linear Model (GLM) regressions of individual wages on a set of workers' characteristics and the establishment female proportion variable.[7] Their results confirm for Canada what has been found for the U.S.: the impact of gender segregation at the establishment level is negative on the wages of both sexes and stronger for the female group.

Finally, Vieira et al. (2003) make use of a data set for Portugal that is similar to the one we employ in our empirical analysis. However, though they have information for various years, their data set is not longitudinal, so their empirical analysis is based on cross-section regressions. Also adding controls for workers' and establishments' characteristics, they found that the effect of establishment female proportion on individual wages is negative for females, but positive for males. This is the only study surveyed here where a positive impact has been found.

In summary, previous research provide support for the conclusion that the effect of working in plants with a predominantly female workforce is negative on the wages of males and females, with this effect being more negative for latter group.

It is important to stress that all previous studies used cross- section data to obtain their results. One of the main motivations for conducting our study was to see whether the finding of a negative effect of establishment female segregation on wages is confirmed by the use of longitudinal data. In section 9.2 we compare our longitudinal results with the cross-section ones obtained in the previous literature and also with our own.

[7] They include a establishment-specific random term which is dealt with through the GLM procedure they use.

Table 1: Characteristics and Findings of Studies on the Relationship Between Establishment Gender Segregation and Wages

Study (1)	Data/Country/Period (2)	Empirical Method (3)	Dependent Variable (4)	Covariates (5)	Establishment Female Proportion Coefficient (6)
1.McNulty (1967)	Occupational Earnings Survey/USA/1966	Comparison of male-female mean wage ratios between integrated establishments and single-sex establishments by occupation	Hourly wage	NA	Janitors in integrated plants: Ratio: 1.18 Janitors in single-sex plants: Ratio: 1.37 Comparison: 1.37/1.18=1.16
2.Buckley (1971)	Occupational Earnings Survey/USA/1970	Comparison of male-female mean wage ratios between integrated establishments and single-sex establishments by occupation	Hourly wage	NA	Unweighted avg in integrated plants: Ratio: 1.11 Unweighted avg in single-sex plants: 1.22 Comparison: 1.22/1.11=1.10
3.Blau(1977, chapter 5)	Area Wage Surveys/USA/1970	Correlation across firm-dummy coefficients from wage and female proportion regressions	NA	Wage regression: sex, occupation and firm dummies Female proportion regression: occupation and firm dummies	Boston: corr = -0.35 New York: corr = -0.27 Philadelphia: corr = -0.26
4.Groshen (1991)	Industry Wage Surveys/USA: Plastics (1974), Machinery (1983), Insurance (1980), Banking (1980), Computer (1983)	Pooled OLS regression	Log hourly wage	Female dummy, female proportion in occupation, establishment, establishment-occupation (job-cell)	Plastics: -0.099 Machinery: -0.330 Insurance: -0.256 Banking: -0.385 Computer: -0.339
5.Carrington and Troske (1995)	Characteristics of Business Owners Survey/USA/1982	Pooled OLS regression at the firm level	Log average employee earnings	Firm size, education and sex of owner, industry dummies, age of firm, firm female proportion (categorical)	Firm percent female: 0%:0.19, 1-9%:0.14, 10-24%:0.36, 25-49%:0.26, 50-74%:0.09, 75-100%: excluded category
6.Carrington and Troske (1998)	Worker-Establishment Characteristics Database/USA/1990	Pooled OLS regression	Log hourly wage	Female dummy, experience, education, marital status, race,occupation dummies establishment size, establishment female proportion, interaction female dummy and establishment female proportion	Men: -0.214 Women: -0.305
7.Bayard, Hellerstein, Neumark, and Troske (1999)	New Worker-Establishment Characteristics Database/USA/1990	Pooled OLS regression OLS regression by sex	Log hourly wage	Female dummy, female proportion in occupation, establishment, establishment-occupation (job cell), human capital variables	Pooled: -0.162 Men: -0.127 Women: -0.157
8.Reilly and Wirjanto (1999)	General Segmentation Survey/Canada/1979	Pooled GLM regression GLM regression by sex	Log hourly wage	Education, experience, tenure, union density, occupation dummies, industry dummies, regional dummies, marital status, establishment female proportion	Pooled: -0.439 Men: -0.223 Women: -0.293
9.Vieira, Cardoso, and Portela (2003)	Ministério da Segurança Social e Trabalho Database/Portugal/1985-1995	OLS regression by sex	Log hourly wage	Education, experience, tenure, industry dummies, occupation dummies, regional dummy, establishment size, establishment female proportion	Men (1985): 0.0296 Men (1995): 0.0344 Women (1985): -0.0393 Women (1995): -0.0283

Notes: All studies are based on cross-section data. NA = Not Applicable.

3 Theoretical Literature

3.1 General Theories

There are basically two main bodies of theory that attempt to explain the existence of gender differences in labour market outcomes: the human capital model and the theories of discrimination. The former is essentially a supply-side story that focuses on the (voluntary) choices made by individuals in terms of both the amount and type of their human capital investments. It provides a consistent explanation for why men and women end up having distinct productivity-related characteristics and careers choices. The latter is a demand-side explanation that is concerned with effects that tastes for discrimination by employers, employees, or customers can have in generating pay and employment differences between equally productive men and women.[8]

The human capital model (Mincer and Polachek, 1974) departs from the traditional gender division of labour within the family under which women are expected to have a shorter and more intermittent attachment to the labour market than men. This implies that, *ceteris paribus*, the net return to investments in formal education for women will be lower than that for men. Similarly, the shorter and more discontinuous labour force participation of women reduces their long-run payoff to investments in general and firm-specific training. Thus, given their shorter expected work life, women's optimal response is to acquire less amount of human capital in education and labour market experience. The implication of this is that part of the gender wage gap we observe is due to the differences between men and women in terms of their productivity-related attributes.

The human capital model also offers a theory of occupational choice (Polachek, 1979, 1981). According to this view women choose occupations that require substantially less investment in on-the-job training and with lower rates of depreciation for periods out of the labour force. Hence, we should expect to observe predominantly female occupations with flatter age-earning profiles.

Closely related to the human capital model are the arguments based on gender differences in preferences and comparative advantages. Individuals may differ in their preferences for a multitude of labour market dimensions: work *versus* leisure, market *versus* non-market work, preferences for certain job characteristics (e.g. flexible *versus* rigid work schedules), etc.[9] Also, it is sometimes argued that the biological differences between the sexes (e.g. physical strength) create comparative advantages that induce women to choose certain types of jobs. The distribution of preferences and comparative advantages for particular types of work and the value to employers of offering distinct job characteristics will influence the shape of the occupational, industrial and interplant wage and employment distributions for males and females. This is at the core of theory of compensating differentials, whereby employers and workers establish a trade between nonpecuniary and

[8] For a thorough survey of the theories of labour market discrimination, see Cain (1986). For a complete and general survey of the theories of gender differences in labor market outcomes, see Altonji and Blank (1999).

[9] One of the most cited sources for the existence of gender differences in preferences is societal discrimination, a process that denotes a host of influences that discriminate women in terms of the roles they are supposed to play in society. This includes child-rearing pursuits, house-keeping activities, and parents influences on shaping their children's preferences to conform to traditional occupations held by each of the sexes. Gender stereotypes may also play an important role in molding individuals' preferences. For example, women are usually believed to be better suitable for tasks that involve caring (nurses, social workers), experience in household-related work (maids, cleaners), manual dexterity (sewers, typists), and attractive physical appearance (receptionist, shop assistant). See Anker (1997, Table 1) for a detailed description of gender stereotypes that are related to the labour market.

pecuniary aspects of the jobs.

The compensating differential argument has been used by Reilly and Wirjanto (1999b) in explaining the negative correlation between the femaleness of establishments and the wages of males and females.[10] More specifically, the authors argue that there may be a "coincidence of needs" between employers and workers that are advantageous for both parts: employers, which use different technologies, offer distinct labour contracts in which lower wages are traded for job characteristics that are typically valued by women (e.g. more flexible hours and child-care friendlier environments). According to this view, the observed sorting of women across establishments and the (compensating) gender wage differential associated with it reflect a mutually advantageous trade between employers and workers that take place in equilibrium. In this sense, policies that try to equalise the wages or change the employment distribution across the sexes are likely to reduce the welfare of workers and firms.

The theories that focus on gender differences in preferences, comparative advantages and (pre-market) accumulation of human capital implicitly interact with the theories of discrimination that we discuss below. For instance, if women perceive that they are discriminated against by employers, this can influence their human capital investment decisions. This point has implications for empirical work, for it makes difficult to separate the effects of labour market discrimination from truly exogenous pre-market factors that produce gender differences in productivity-related attributes. More specifically, this interaction implies that analyses that take such variables as education and experience as truly exogenous may underestimate the extent of labour market discrimination.

There are two main classes of models of labour market discrimination. The first is based on the idea that some individuals of the majority group (men, whites) have tastes against interacting with individuals of the minority group (women, blacks). The second is statistical discrimination, wherein the existence of imperfect information about the skills of workers and the formation of beliefs about the sexes' average quality lead employers to statistically discriminate the minority group.[11]

The foundations of labour market discrimination theory were laid out by Becker (1971). There are three flavours of this theory depending on whether discriminatory tastes originate from employers, employees, or customers. In all cases, it is assumed that males and females are equally productive (i.e. they are perfect substitutes in production), so the wages of men and women should be equal in the absence of discrimination. Further, in all models firms operate in competitive product and input markets.

In its simplest form, Becker's model of employer discrimination postulates that there are homogeneous employers that maximise a utility function that is composed of the sum of two parts: profits and the (monetary) value from hiring the minority group (females). More specifically, the representative firm maximises

$$u = f(M + F) - w_M M - w_F F - dF \tag{1}$$

where $f(.)$ represents the production function, M and F denote the employment level of males and females, w_g, $g = M, F$, is the wage paid to gender g, and $d > 0$ represents the taste parameter of discrimination against females (termed "discrimination coefficient" by

[10] See also Reilly and Wirjanto (1999a).

[11] Though our presentation of discrimination models is focused on gender discrimination, it also applies, *mutatis mutandis*, to race discrimination.

Becker).[12] From the first-order conditions (FOC) we obtain

$$f_M = w_M \tag{2}$$

and

$$f_F = w_F + d \tag{3}$$

where f_g, $g = M, F$, represents the marginal product of gender g. Note that (3) implies that females are paid less than their marginal product.

Because males and females are interchangeable in production, we have that $f_M = f_F = f_L$, where $L = M + F$. Hence, from (2) and (3), it must be that

$$w_M - w_F = d > 0, \tag{4}$$

so as expected equilibrium requires that male wages exceed female wages. Since all firms are identical, they all hire the same amounts of male labour and female labour. The implications of this are that the allocation of labour is efficient, and the effects of discrimination are purely distributive.

Arrow (1973b) generalised Becker's model of employer discrimination. He worked with a general form for the firm's utility function, and allowed firms to have heterogeneous tastes for discrimination against females and in favour of males. Now firms maximise $U(\pi, F, M)$, where π denotes profits. The marginal rates of substitution of profits for females and males are given respectively by $d_F = -U_\pi/U_F$ and $d_M = -U_\pi/U_M$. It is assumed that $U_F \leq 0$ and $U_M \geq 0$, so that employers derive negative (positive) marginal utility from hiring females (males). From the FOC we now have that $f_M = w_M + d_M$ and $f_F = w_F + d_F$ implying that

$$w_M - w_F = d_F - d_M > 0, \tag{5}$$

so again there appears an equilibrium wage gap between males and females. The effects of discrimination on profits can be calculated by comparing the profit levels in the discriminatory and non-discriminatory environments. In the former case, profits can be written as $\pi_D = f(L) - f_L L + d_M M + d_F F$; in the latter case, profits are $\pi_{ND} = f(L) - f_L L$. Hence, the change in profits is

$$\pi_D - \pi_{ND} = d_M M + d_F F. \tag{6}$$

Equation (6) can be interpreted as the amount of profits required to compensate the employer for a marginal increase in his/her labour force that preserves its sex composition. A plausible hypothesis considered by Arrow is that employer's utility depends only on the ratio of females to males workers.[13] This implies that the firm neither increases nor decreases its profits from discriminating against females and/or favouring males, that is

$$d_M M + d_F F = 0. \tag{7}$$

Equations (5) and (7) constitute a system of linear equations in d_M and d_F that, when solved, gives the following relationships for the proportion of males and females in the firm:

$$M/L = d_F/(w_M - w_F) \quad and \quad F/L = -d_M/(w_M - w_F). \tag{8}$$

[12] In Becker's model there is a second parameter that reflects discrimination in favour of males ("nepotism coefficient"). Below we present Arrow's generalization of Becker's model in which this coefficient is included.

[13] This hypothesis is equivalent to the assumption that the utility function is homogeneous of degree zero.

This last expression tells us that the proportion of females across firms will vary according to their "degree" of discriminatory behaviour: the less (more) discriminatory the employer is, the higher (lower) the proportion of females in the firm. It should be observed that in contrast to Becker's model the marginal product of labour is not the same across firms, which implies that the allocation of labour ceases to be efficient.

One of the drawbacks of the employer's discrimination model is that its implications may not be persistent in the long run. Indeed, in this model the less discriminatory firms have lower costs of production (they can hire relatively more of the less expensive female labour), and thus can expand their activities and push the more discriminatory firms out of the market in the long run.[14] If the supply of women is relatively small compared to the labour demand for women from the less discriminatory firms, then their wages may rise to the point where the gender wage differential is eliminated. Implicitly in this reasoning is the conflict between utility- and profit- maximising behaviour of firms that operate in competitive markets. In other words, competitive pressures will drive out those employers that are more willing to "indulge" themselves by sacrificing money profits for their discriminatory tastes.

Some possibilities have been proposed in the literature to solve the long-run problem embodied in the employer's discrimination model. Some of them will be discussed below within the Becker/Arrow's framework of employee and customer taste-based discrimination. Other possibilities are based on arguments of non-competitive markets. First, since monopolistic firms tend to have above-competitive profits, they are able to exchange money profits for the psychic gains from discrimination. In that case, discrimination tends to be more severe, on average, in monopolistic than in competitive industries.[15] Second, it has also been proposed that monopsony power by employers can sustain the long-run existence of a gender pay differential (Madden, 1973). As it is well known, in this setting employers face an upward-sloping supply curve of labour. At the optimum they equate the marginal revenue product of labour to their (increasing) marginal labour costs to determine their corresponding optimal labour demand. Wages, which are determined by the supply curve, are then smaller than the marginal revenue product, so employers obtain positive profits. If it assumed that the labour supply of women is less elastic than that of men, then there will appear a gender wage gap, all else equal.

One problem with the monopsonistic explanation is that it is based on differences in the labour supply behaviour of the two gender groups. It has been argued that the labour supply of women tends to be less responsive to changes in wages because of factors such as occupational segregation, less engagement in job search, or the seeking for jobs that are closer to home (Madden, 1973). However, other arguments have been proposed that could increase the women's labour supply elasticity. For instance, it could be that the availability of home work provides an alternative activity to women, at least for those that are at the margin of labour force participation. In addition, if women have higher mobility than men because they acquire less firm-specific training, this will contribute to increase their labour supply elasticity (Blau and Jusenius, 1976). Clearly, whether there is a difference in the labour supply elasticities of men and women is an empirical matter. In fact, although there is a great deal of evidence that the aggregate labour supply elasticity of women is higher than that of men, less is known about the differences in labour supply to individual employers.[16] Moreover, explaining the existence of gender pay differentials

[14] This may result either from an assumption of free entry or that the production function displays constant return to scale.

[15] There is some empirical support for this prediction. See Ashenfelter and Hannan (1986).

[16] Using a job-search model of monopsonistic competition, Manning (2003, ch. 7) shows that it is unclear

using the discrepancy in the labour supply behaviour of the two groups introduces a second argument that seems somewhat alien to the main argument being proposed, namely the existence of discriminatory behaviour of employers. In other words, the existence of gender pay gaps can be explained by the differences in labour supply between men and women even if employers do not discriminate against women.

It is important to stress that the Becker/Arrow's model is a perfectly competitive model (i.e. all firms are price takers). Therefore, since there is only one pair of market clearing wages for males and females, the only margin of adjustment the firms have is to choose their optimal level of employment for males and females. Below we set up a model in which we embed Becker/Arrow's model in a monopsonistic framework. This allows firms to pay different wages and choose different sex compositions of their labour forces.

Both Becker and Arrow also considered the case of employee discrimination. In this setting male employees have tastes for discrimination against women and require a wage premium that is sufficient to induce them to work with female co-workers. There are two variants of this model. In the first there is a third factor of production (such as supervisors) which is complementary to both male and female labour. These supervisors are assumed to have discriminatory tastes against working with women. Further, it is assumed that each supervisor chooses among employment opportunities taking into consideration an inverse preference trade-off between wages and the ratio of males to females in the firm. Then, it can be proved (see Arrow (1973a)) that employers will not pay their female workers the same wage they pay to their male workers, and thus a wage differential emerges.[17] This variant of the model has no clear prediction about the amount of sex segregation across firms: all firms can end up having the same level of employment for the three types of labour they hire, but it is also conceivable that there may appear different "niches" of firms characterised by different ratios of females to males workers (Arrow, 1973a, p. 116).

In the second flavour of the employee discrimination model there is no third factor of production, but it is assumed that male workers possess discriminatory tastes against working with female co-workers. Now, it is the male co-workers that have preferences that display a negative trade-off between wages and the male proportion in the firm. In that case, all firms are completely segregated and there is no gender wage differential. The arguments that prove these predictions can be summarised as follows. First, note that the wage required by males to work in an all-male firm is always smaller than the required wage to work in an integrated firm. This is due to the discriminatory-based inverse relationship between male wages and the proportion of males in the firm. Given this, consider two polar cases. If the wage required by males to work in an all-male firm is higher than females wages, then the cheapest choice for the firm is to hire only females; if the opposite case happens - i.e. the required male wage to work in an all-male firm is lower than female wages - then the firm's optimal choice is to hire only males. Since this is a full employment model, equilibrium then requires that the wages of males and females are equal. Thus, because integrated firms would have to pay higher wages to their male employees, at equilibrium every firm is segregated and there is no wage differential between the males and females.

The third model of discrimination considered by Becker and Arrow is based on customer's discrimination. Clients who have tastes for discrimination against females act as though there is a non-pecuniary cost associated with purchasing a product from a woman. As a result, they will only buy the product sold by women at a lower price. This implies

whether the elasticity of female labour supply to an individual firm is higher or lower than the corresponding male elasticity.

[17] Clearly, increasing the number of females increases the cost of this third factor, thus increasing the firm's costs. The reverse statement applies for increasing the number of males.

that employers may discount female wages to compensate them for the lower revenues that female sellers entail. Clearly, this model seems to be relevant only for those industries where there is significant customer contact with sellers, such as in services and trade sectors.

As aforementioned, one interesting feature of the models of employee or customer discrimination is that they are compatible with competitive equilibrium in the long run. Indeed, since in both of these models the discriminatory behaviour does not stem from the firms' preference structure, their profit-maximising behaviour is not affected. Hence, competitive pressures may co-exist with discrimination and long-lasting gender pay differentials.

As mentioned in the introduction to this paper, most of the empirical literature focuses on gender differences in labour market outcomes across occupations (and to a lesser extent among industries). Becker/Arrow's formulation can be accommodated to be compatible with the existence of gender pay differentials and gender segregation in these dimensions. In fact, Bergmann (1974) has developed a theory in the Becker/Arrow tradition - the so-called "overcrowding" model - in which discrimination against females leads to segregation of men and women into two sets of sectors (e.g. occupations).[18] It is assumed that there is no free mobility of labour between these two sectors. Hence, if job opportunities in the female sector are small relative to their labour supply, then women will "crowd" to obtain work in this sector, depressing the wage there. This may then lead to the appearance of male-female pay differential.

All previous models of discrimination were based on the hypothesis that the members of the majority group possess discriminatory tastes against the minority group. The second class of models of labour market discrimination does not depart from this assumption. Instead, the motivation of employers for discrimination hinges on the hypothesis that they have imperfect information about the productivity of applicant workers. In this case, employers may have incentives to use easily observable characteristics of individuals (e.g. sex or race) to statistically discriminate among workers. There are two types of models in the statistical discrimination literature. The first relies on the premise that employers discriminate against women because their productivity is less reliably predicted than that of males (Phelps, 1972; Aigner and Cain, 1977; Lundberg and Startz, 1983). The second is based on the idea that employers discriminate against women because they hold prior beliefs about the expected productivity of each sex group (Arrow, 1973b; Coate and Loury, 1993). Since they are based on the existence of imperfect information, these models of statistical discrimination provide another way through which discrimination can co-exist with profit-maximising behaviour of employers.

A simple model of the first type has been postulated by Lundberg and Startz (1983). In their model, a worker's true productivity, p, is given by the sum of two random components: $p = a + be$, where a and e represent respectively innate and acquired ability, and b is a positive scalar. In choosing e workers equate the marginal increment in wages to the marginal cost of obtaining e, the latter assumed to be linear (i.e. $c'(e) = ce$, with c being a positive scalar common to all workers). Employers base their hiring decisions on some indicator of labour productivity, t, which measures the true productivity of workers with a random error: $t = p + u$. In determining the equilibrium of this model, workers decide the optimal amount of investments in e looking to the wage offer schedule that firms derive by

[18] This may occur because employers, co-workers, or customers are prejudiced against women in only some occupations, or because males and females have different preferences and abilities for certain types of jobs, or from the socialization process.

looking to the joint distribution of p and t.[19] It is assumed that the unobservable terms a and u are independently normally distributed. Employers pay wages equal to the expected productivity of workers, so that $w = E[p|t] = t - E[u|t]$. Then, it can be shown that workers face the wage schedule $w = \bar{p} + \beta(t - \bar{t})$, where β is a fixed parameter that depends on other parameters of the model.[20] Since marginal increases in e rise p and t by the scalar b, the individual return to investments in e is $b\beta$, implying that the equilibrium level of acquired ability is $e = \beta b/c$. This means that e is non-stochastic in equilibrium, which, as the authors show, implies that $\beta = \sigma_a^2/\sigma_t^2 = \sigma_a^2/(\sigma_a^2 + \sigma_u^2) < 1$.

Consider the situation in which males and females have identical mean innate ability, $\bar{a}$, the same mean of the random measurement term, $\bar{u}$. Suppose that the two groups differ in that either $\sigma_{aM}^2 > \sigma_{aF}^2$ or $\sigma_{uM}^2 < \sigma_{uF}^2$, that is, there is either relatively more heterogeneity in males' innate ability or relatively more homogeneity in the reliability with which their productivity is measured. In either case, the wage schedule for males and females will be different, with $\beta_M > \beta_F$, so that employers rationally discriminate between the two groups. Since the net marginal return to extra units of e is higher for males than females ($\beta_M b/c > \beta_F b/c$), in equilibrium the former group obtains more acquired ability than the latter (i.e. $\overline{e_M} > \overline{e_F}$). As a consequence of this, the average productivity of males is higher than that of females, implying that male wages are on average larger than female wages.

Figure 1 (which is based upon Fig. 2 from Lundberg and Startz (1983)) depicts the wage schedule for each group. Since $\beta_M > \beta_F$, the male wage schedule is steeper than the female one, meaning that males receive larger wage raises for the same increment in the value of the productivity indicator measure. Also, because $\overline{t_M} > \overline{t_F}$, males have higher average wages than females, resulting in the appearance of a male-female wage differential in equilibrium.[21] It is interesting to note that, since workers are paid according to their expected marginal productivity, and the average wage for each group is equal to the average marginal product of the group, an economist may consider this situation a non-discriminatory equilibrium. However, if one defines economic discrimination for situations where groups with identical average innate ability do not receive equal wages in equilibrium (Lundberg and Startz, 1983, p. 342), then the labour market equilibrium displayed in this model is characterised by the existence of economic discrimination.[22]

The second type of models of statistical discrimination can be exemplified using Arrow (1973b). There are two kinds of jobs in a firm, unskilled and skilled, which are complementary to each other. All workers are qualified to perform unskilled jobs, but only some workers can hold skilled positions. It is assumed that employers do not know beforehand the productivity of any individual worker and that they must incur some investment costs (e.g. a trial period) when hiring workers for skilled positions. It is also assumed that employers have a preconception about the productivity distribution for males and females. Specifically, they to hold beliefs that a random male is qualified for a skilled job with probability p_M, and a random female with probability p_F. Let mp_S be the marginal productivity of skilled workers, and r the expected return per worker on the investment employers make to determine the true productivity of the worker. It is assumed that the net gain to the employer of hiring a worker that turns out to be unskilled is nil. If employers

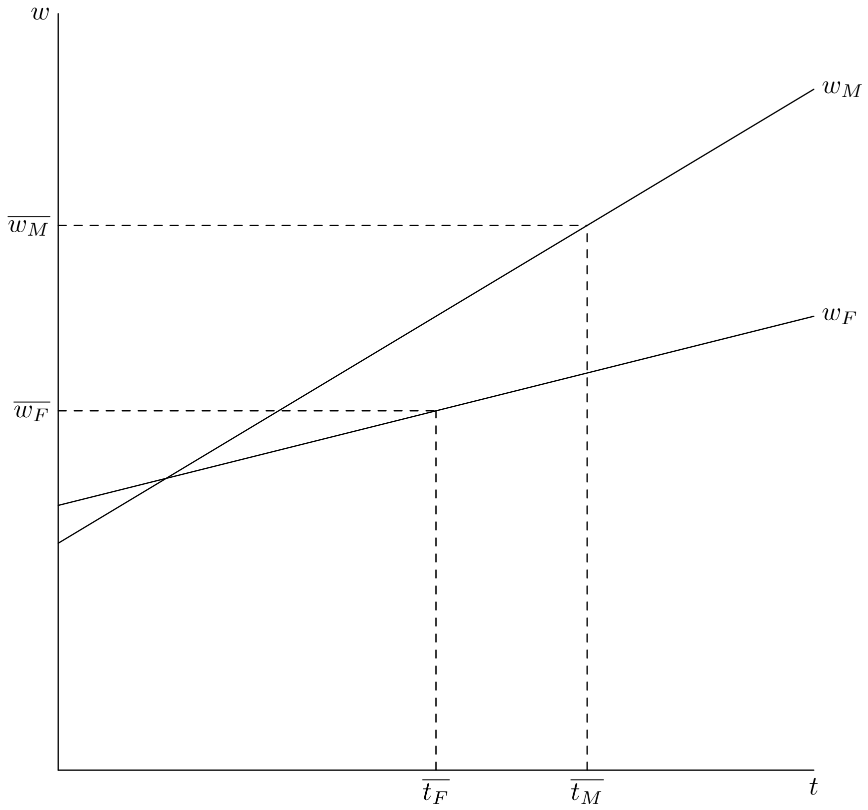
[19]The parameters characterising the (joint) distributions of the random variables in this model are assumed to be known. The parameters b and c are also are also taken be public knowledge.

[20]See Lundberg and Startz (1983, p.343) for the derivation of this result.

[21]Given that males and females are assumed to have identical $\bar{a}$ and the same $\bar{u}$, the fact that $\overline{e_M} > \overline{e_F}$ leads to $\overline{p_M} > \overline{p_F}$, thus $\overline{t_M} > \overline{t_F}$.

[22]See Aigner and Cain (1977) for a discussion of different definitions of labour market discrimination.

Figure 1: Wage Offer Schedules for Males (M) and Females (F)



are risk-neutral, then it must be that

$$r = (mp_S - w_M)p_M = (mp_S - w_F)p_F, \tag{9}$$

where w_g is the wage paid to a qualified worker of gender $g = M, F$. Let $q = p_F/p_M$, thus

$$w_M = qw_F + (1-q)mp_S. \tag{10}$$

If employers' beliefs are such that $p_M > p_F$, then equation (10) shows that the w_M is a convex combination of w_F and mp_S. Noting that $w_F < mp_S$ (so that employers can recover the investment he/she makes in determining the productivity of workers, see equation (9)), it follows that $w_M > w_F$, that is, there appears a wage differential between males and females.

One important issue regarding this model is why employers sustain different beliefs about the probabilities that males and females are qualified. Arrow has argued that one possible explanation relies on the theory of cognitive dissonance[23], a process by which beliefs and actions come into an equilibrium where discriminatory acts give rise to discriminatory beliefs which, by their turn, justify the initial discriminatory acts. These feedback effects may then give rise to a socio-economic equilibrium in which there is a perpetuation of discrimination in the long run. Arrow also rises a more economic-based explanation which allows workers' qualification decisions to be endogenous, that is, workers decide to

[23]Arrow cites (Arrow, 1973b, p. 159) the theory developed by Festinger, Leon (1957): *A Theory of Cognitive Dissonance*, Row Peterson, Evaston, Illinois. See Akerlof and Dickens (1982) for a discussion and a model of how cognitive dissonance may produce economic effects.

invest in themselves by considering the gains from qualifying.[24] Arrow (1973a,b) shows that, although a symmetric, non-discriminatory equilibrium is possible, this equilibrium may not be stable. The argument for this instability is simple. Departing from the non-discriminatory equilibrium, suppose that the proportion of qualified males becomes slightly higher than that of females. Then, there will appear a gender wage gap, which will give males (females) a higher (lower) incentive to invest in their qualifications. This will amplify the initial existing wage disparity, leading to a sort of self-confirming equilibrium in which employers' perceptions of gender differences in qualifications are corroborated by the actual evidence on the two group's differential performances. Naturally, a sex wage differential will arise.[25]

In the empirical analysis we present below we are interested in the relationship between sex segregation at the firm level and the wages of males and females. Apart from the Becker/Arrow's framework of employer discrimination, none of the models presented above deals explicitly with this relationship. In what follows, we set up two different models that explicitly consider this relationship. However, before we do that it is worth bringing up a piece of theory that has been frequently mentioned in the literature but never formalised, the so-called quality sorting hypothesis (Macpherson and Hirsch, 1995; Carrington and Troske, 1998; Reilly and Wirjanto, 1999a). Its idea is simple and based on two premises: the first is that firms are heterogeneous in terms of the skill requirements they have; the second is that women and men have different skill levels, with the former group being less qualified. The result is that firms that require relatively more unskilled (skilled) labour will have a higher (lower) concentration of females and pay lower (higher) wages. Accordingly, this theory predicts that the wages of men and women are negatively correlated with the proportion of females in the firm. In one of the models we present below we formalise these ideas in a more general framework of statistical discrimination. In our first model, however, we take a different route: we embed the Becker/Arrow's model of employer discrimination in a monopsonistic framework.

3.2 Employer Discrimination in a Monopsonistic Labour Market

As in the Becker/Arrow's framework, employers have heterogeneous discriminatory tastes against hiring females. Firms operate in a monopsonistic labour market, so the labour supply to the individual firm is positively sloped. In addition, it is assumed that the supply of male and female labour to the firm is identical.[26] Furthermore, we assume that firms possess heterogeneous technologies whose only input is labour. Males and females are considered perfect substitutes in production.

Giving these assumptions, a firm $j = 1, ..., J$ maximises its utility function choosing the amount of males, M, and females, F, according to

$$\max_{M_j, F_j} u_j = f(M_j + F_j, \theta_j) - w_{jM}(M_j)M_j - w_{jF}(F_j)F_j - d_jF_j, \tag{11}$$

[24]This investment is not perfectly observed by employers, so it should encompass the acquisition of unobservable abilities such as work habits (e.g. initiative, responsiveness, etc.).

[25]Coate and Loury (1993) also present a model of statistical discrimination where *ex-ante* employers' beliefs about the skills of the two groups are confirmed in equilibria in which the *ex-post* levels of skills of the groups are in fact different.

[26]We make this assumption for two reasons: first because there is no consolidated evidence that the labour supply elasticities to the firm of the two sex groups are different; second because we do not want to confound the effects of discrimination with the effects generated by differences in the labour supply behaviour of males and females.

where $f(.)$ is a well behaved production function, and $w_{jM}(.)$ and $w_{jF}(.)$ represent the labour supply to the firm of males and females respectively. The heterogeneity in production across the firms is represented by the parameter $\theta_j > 0$, and the heterogeneity in discrimination against females is captured by the parameter $d_j > 0$.

Let $L_j = M_j + F_j$. Dropping the j subscript the FOC are

$$\frac{\partial u}{\partial M} = f_L(L^*(\theta,d),\theta) - w'_M(M^*(\theta,d))M^*(\theta,d) - w_M(M^*(\theta,d)) \equiv 0 \tag{12}$$

and

$$\frac{\partial u}{\partial F} = f_L(L^*(\theta,d),\theta) - w'_F(F^*(\theta,d))F^*(\theta,d) - w_F(F^*(\theta,d)) - d \equiv 0 \tag{13}$$

where $f_L \equiv \frac{\partial f}{\partial L}$ and $w'_g \equiv \frac{\partial w_g}{\partial g}$, $g = M, F$.

From the FOC we can analyse how the demands for males and females respond to changes in the technological and discrimination parameters:

$$\frac{\partial M^*}{\partial \theta} = \frac{f_{L\theta}[w''_F F^* + 2w'_F]}{\Delta_2} \tag{14}$$

$$\frac{\partial F^*}{\partial \theta} = \frac{f_{L\theta}[w''_M M^* + 2w'_M]}{\Delta_2} \tag{15}$$

$$\frac{\partial M^*}{\partial d} = \frac{-f_{LL}}{\Delta_2} \tag{16}$$

$$\frac{\partial F^*}{\partial d} = \frac{\Delta_1}{\Delta_2} \tag{17}$$

where $\Delta_1 = f_{LL} - w''_M M^* - 2w'_M < 0$ and $\Delta_2 = (f_{LL} - w''_M M^* - 2w'_M)(f_{LL} - w''_F F^* - 2w'_F) - (f_{LL})^2 > 0$.[27] Thus, since the labour supply curves to the firm are positively sloped (i.e. $w'_g > 0$, $g = M, F$), the demand for male and female labour will increase with θ if two (sufficient) conditions are met, specifically $f_{L\theta} > 0$ and $w''_g \geq 0$, $g = M, F$. The first condition seems a reasonable assumption since it holds for usual specifications of the production function. The second condition, which requires that labour supply functions be convex, holds for the linear case. At the cost of loosing some generality but for the sake of simplicity, below we will assume that the labour supply functions are linear. As expected, the more discriminatory the employer is against females (i.e. the higher d), the higher (lower) the demand for males (females).

At this level of generality it is difficult to obtain closed-form expressions that allow a direct analysis of the relationship between sex segregation at the firm level and the wages paid to males and females. Thus, we simplify the above setting by making some functional form assumptions. Suppose then that

$$f(L) = C + \theta L - L^2/2, \qquad C > 0,\ \theta > 0 \tag{18}$$

and

$$w_g = \alpha + \frac{\beta}{2} g, \quad g = M, F,\ \alpha > 0,\ \beta > 0. \tag{19}$$

From the FOC (12) and (13) we can obtain the optimal demand for males and females, which are given respectively by

$$M^*(\theta,d) = \frac{(\theta - \alpha)\beta + d}{\beta(2+\beta)} \tag{20}$$

[27] The signs of Δ_1 and Δ_2 are given by utility maximisation conditions.

and

$$F^*(\theta, d) = \frac{(\theta-\alpha)\beta - (1+\beta)d}{\beta(2+\beta)}. \tag{21}$$

For future reference we note that if a firm is to hire female labour at all (i.e. if $F^*(\theta, d) > 0$) it must be that

$$\theta - \alpha > \frac{1+\beta}{\beta} d > 0. \tag{22}$$

The optimal wage paid to males and females by any specific firm is given respectively by[28]

$$w(M^*(\theta, d)) = \frac{2\alpha(2+\beta) + (\theta-\alpha)\beta + d}{2(2+\beta)} \tag{23}$$

and

$$w(F^*(\theta, d)) = \frac{2\alpha(2+\beta) + (\theta-\alpha)\beta - (1+\beta)d}{2(2+\beta)}. \tag{24}$$

In order to analyse the connection between sex segregation at the firm level and the wage it pays to its male and female employees we postulate the existence of a relationship between the discriminatory behaviour of the firm and its productivity parameter. More specifically, suppose that

$$d = m(\theta - \alpha) = m(\theta^*), \tag{25}$$

where $\theta^* = \theta - \alpha$ and $m(.)$ is an unknown function, which is only assumed to be continuously differentiable. Then, from equations (23) and (24) we can write the optimal wages paid to males and females respectively as

$$w_{M^*} = \frac{2\alpha(2+\beta) + (\theta-\alpha)\beta + d}{2(2+\beta)} = \gamma_1 + \gamma_2\theta^* + \gamma_3 m(\theta^*) \tag{26}$$

and

$$w_{F^*} = \frac{2\alpha(2+\beta) + (\theta-\alpha)\beta - (1+\beta)d}{2(2+\beta)} = \gamma_1 + \gamma_2\theta^* - \gamma_4 m(\theta^*), \tag{27}$$

where $\gamma_1 = \alpha$, $\gamma_2 = \frac{\beta}{2(2+\beta)} > 0$, $\gamma_3 = \frac{1}{2(2+\beta)} > 0$, and $\gamma_4 = \frac{(1+\beta)}{2(2+\beta)} > 0$.

Defining the feminisation degree of a firm as the ratio between the demand for females and for males we can write it as

$$\begin{aligned} \frac{F^*}{M^*} &= \frac{(\theta-\alpha)\beta - (1+\beta)d}{(\theta-\alpha)\beta + d} \\ &= \frac{\frac{\theta^*}{d} - \frac{1+\beta}{\beta}}{\frac{\theta^*}{d} + \frac{1}{\beta}} = 1 - \frac{\frac{2+\beta}{\beta}}{\frac{\theta^*}{d} + \frac{1}{\beta}} \\ &= r\left(\frac{\theta^*}{d}\right) = r\left(\frac{\theta^*}{m(\theta^*)}\right). \end{aligned} \tag{28}$$

We can now see how the wages of males and females vary with the feminisation degree of the firm. We have that

$$\frac{dw_{M^*}}{d(\frac{F^*}{M^*})} = \frac{\gamma_2 + \gamma_3 m'}{r'.\left(\frac{m - \theta^* m'}{m^2}\right)} = \frac{m^2(\gamma_2 + \gamma_3 m')}{r'.(m - \theta^* m')} \tag{29}$$

[28] There are at least two monopsonistic theories that predict the existence of wage dispersion across firms in equilibrium. The first is the search-based framework of Burdett and Mortensen (1998), and the second is the location-based model developed by Bhaskar and To (2003). Manning (2003) and Bhaskar et al. (2002) offer reviews of this type of models.

and

$$\frac{dw_{F^*}}{d(\frac{F^*}{M^*})} = \frac{\gamma_2 - \gamma_4 m'}{r'.\left(\dfrac{m - \theta^* m'}{m^2}\right)} = \frac{m^2(\gamma_2 - \gamma_4 m')}{r'.(m - \theta^* m')}, \tag{30}$$

where $r' = \frac{\partial r(\frac{\theta^*}{d})}{\partial(\frac{\theta^*}{d})} = \frac{\frac{2+\beta}{\beta}}{\left(\frac{\theta^*}{d}+\frac{1}{\beta}\right)^2} > 0$. Thus, to find out the direction of $\frac{dw_{M^*}}{d(\frac{F^*}{M^*})}$ and $\frac{dw_{F^*}}{d(\frac{F^*}{M^*})}$ we need to study the signs of three terms: (i) $[\gamma_2 + \gamma_3 m']$, (ii) $[\gamma_2 - \gamma_4 m']$, and (iii) $[m - \theta^* m']$. The sign of the first term is given by

$$\gamma_2 + \gamma_3 m' \gtrless 0 \Leftrightarrow m' \gtrless -\frac{\gamma_2}{\gamma_3} = -\beta < 0, \tag{31}$$

whereas the sign of the second term by

$$\gamma_2 - \gamma_4 m' \gtrless 0 \Leftrightarrow m' \lessgtr \frac{\gamma_2}{\gamma_4} = \frac{\beta}{1+\beta} > 0. \tag{32}$$

As for the third term

$$m - \theta^* m' \gtrless 0 \Leftrightarrow m' \lessgtr \frac{m}{\theta^*} = \frac{d}{\theta^*} = \frac{d}{\theta - \alpha} < \frac{\beta}{1+\beta}, \tag{33}$$

where we have used the definitions of θ^* and m (see equation (25)), and the last inequality follows from the result that if a firm hires any female workers we must have that $\theta - \alpha > \frac{1+\beta}{\beta} d$ (see expression (22)).

These last three results show that the signs of $\frac{dw_{M^*}}{d(\frac{F^*}{M^*})}$ and $\frac{dw_{F^*}}{d(\frac{F^*}{M^*})}$ can be obtained by looking to the values assumed by m'. Table 2 gives the possible cases for the signs we are interested in. As it can be seen from the Table, depending on the value of the parameters of the model (α, β, θ, d) and the value of m', the wages of males and females may vary positively or negatively with the feminisation degree of the firm. Indeed, there may be sets of parameter values for which the variation in the relationship between discrimination and productivity (i.e. $\frac{dd}{d\theta^*} = m'$) is such that: (i) the wages of males (females) vary negatively (positively) with the feminisation degree (cases A and D), (ii) both the male and female wages increase with the feminisation degree (case B), and (iii) rises in the feminisation degree reduce the wages of males and females (case C). This last case is the one compatible with the empirical evidence of the cross-section literature (see section 1.2).

In summary, insofar as the labour market can be reasonably well described by monopsonistic theory and there is an association between how much a firm discriminates against females and its unobserved productivity, the model presented above offers a simple framework to understand the effect of female segregation at the firm level on the wages of males and females. The model's results show that this effect may be positive or negative depending on the unobserved characteristics of the firms (i.e. the value of the parameters θ and d), the labour supply parameters (i.e. α and β), and the "strength" of the connection between employers' discriminatory tastes and their productivity (i.e. m'). It is interesting to note that, although we have imposed some functional form assumptions, the predictions of the model are sufficiently general to encompass various possible signs for the effect of interest.

3.3 Quality Sorting and Statistical Discrimination

We now turn to the model which combines the ideas of quality sorting and statistical discrimination. As aforementioned, the quality sorting hypothesis is based on the assumptions that firms have different relative demand for skilled labour, and that workers are

Table 2: The Signs of $\frac{dw_{M^*}}{d(\frac{F^*}{M^*})}$ and $\frac{dw_{F^*}}{d(\frac{F^*}{M^*})}$

Value of $m'(\theta^*)$	Case A $(-\infty, -\beta)$	Case B $[-\beta, \frac{d}{\theta^*})$	Case C $[\frac{d}{\theta^*}, \frac{1+\beta}{\beta})$	Case D $[\frac{1+\beta}{\beta}, +\infty)$
$\gamma_2 + \gamma_3 m'(\theta^*)$	$-$	$+$	$+$	$+$
$\gamma_2 - \gamma_4 m'(\theta^*)$	$+$	$+$	$+$	$-$
$m(\theta^*) - \theta^* m'(\theta^*)$	$+$	$+$	$-$	$-$
$\frac{\partial w_{M^*}}{\partial(\frac{F^*}{M^*})}$	$-$	$+$	$-$	$-$
$\frac{\partial w_{F^*}}{\partial(\frac{F^*}{M^*})}$	$+$	$+$	$-$	$+$

sorted across firms according to their skills. In its simplest form this theory assumes that women are less qualified than men (see Carrington and Troske (1998)), so firms whose relative demand for skilled workers is lower will have a higher female proportion and pay lower (average) wages to their workers. Here, we formalise these ideas but, instead of simply assuming that women are less qualified than men, we develop a simple statistical discrimination framework that leads to the result that the latter (former) group will be over(under)-represented in skilled jobs. Some of the ideas we formalise here were initially suggested by Reilly and Wirjanto (1999a).

There is a fixed number of firms (J) in the market, where each firm j has a fixed amount of capital, k_j. The technology used by all firms requires two types of labour, skilled (s) and unskilled (u), where each unit of capital (e.g. a machine) requires a fixed number of workers of each type. Let s_j and u_j denote these fixed numbers for skilled and unskilled labour, respectively. We can then express the (fixed) aggregate demand for each type of labour as

$$N_s = \sum_{j=1}^{J} s_j k_j \tag{34}$$

and

$$N_u = \sum_{j=1}^{J} u_j k_j. \tag{35}$$

Males (M) and females (F) supply labour in the market. Workers have different levels of innate ability and acquire skills (e.g. education), which are relevant to production. Employers do not observe the true productivity of workers but they do observe their level of acquired skills, which we denote by e. Employers separate out those workers that will hold skilled and unskilled jobs by fixing minimum levels of e above which workers are hired to skilled positions. It is assumed that employers hold beliefs that the minimum skill level

for a random male to be qualified for a skilled position is lower than the minimum level for a random female, that is, $\overline{e_M} < \overline{e_F}$, where the over-bar denotes the fixed thresholds of e.[29] Hence, women have to acquire relatively more skills than men so as to signal to employers that they are qualified enough to get a skilled position. In fact, however, females are as productive as males, so despite the fact that $\overline{e_F} > \overline{e_M}$ females generate the same output as males in skilled positions. The same applies to unskilled jobs.

There is a fixed number of workers (T) supplying labour in the market. Workers can be in one of three labour market statuses: unemployment, working in an unskilled job, or holding a skilled position. All workers are assumed to have the same reservation wage, $\overline{w_r}$. In choosing which status they prefer to be in, workers also look to the market wages for unskilled and skilled jobs, which are respectively denoted by w_u and w_s. We assume there is excess supply of labour (i.e. $T > N_s + N_u$), which implies that in equilibrium the unskilled wage will be equal to the reservation wage of workers: $w_u^* = \overline{w_r}$. Thus, workers become indifferent between being unemployed or holding an unskilled job.

Males and females are assumed to have identical innate ability distributions, where the former group represents α% and the latter $(1-\alpha)$% of the labour force. Workers have the same cost function to acquire the skills that are relevant to production. More specifically, the cost of acquiring those skills is given by

$$C = C(a, e), \tag{36}$$

where a represents the level of innate ability. We make the following assumptions about the cost function $C(.,.)$. First, it is assumed that

$$C(a, 0) = 0 \tag{37}$$

for all levels of a. Second, workers with higher innate ability levels have lower costs to acquire skills:

$$\frac{\partial C}{\partial a} < 0. \tag{38}$$

Third, the higher the skill level the worker decides to obtain the higher its costs:

$$\frac{\partial C}{\partial e} > 0. \tag{39}$$

Fourth, it is assumed that for any skill level e the increase in costs to acquire additional skills is lower for those with higher ability, that is

$$\frac{\partial^2 C}{\partial a \partial e} < 0. \tag{40}$$

Workers decide to invest in acquiring skills by comparing the costs of this investment to its return, that is, they look to whether $C(a, e) \gtrless w_s - w_u$. Since (i) the cost of acquiring skills is increasing in the level of skills (see assumption (39)), and (ii) the minimum level of skills established by employers for skilled jobs, workers choose either to acquire no skills at all or the minimum level. Given that this minimum level is different across the gender groups, males and females who decide to obtain a positive amount of skills choose $\overline{e_M}$ and $\overline{e_F}$, respectively.

[29]There may be some reasons underlying the employers' discriminatory behaviour. For instance, if employers think that females are, on average, more "talkative" at the work place than males, then they react to that by demanding a higher skill level from females in order to hire them for skilled jobs.

Let the lowest ability male and female who decide to acquire the minimum skill levels for a skilled job be respectively defined by a_M and a_F. More formally, those workers can be implicitly defined by

$$C(a_M, \overline{e_M}) = w_s - w_u \tag{41}$$
$$C(a_F, \overline{e_F}) = w_s - w_u. \tag{42}$$

In other words, those are the marginal workers who are indifferent between whether or not to invest in acquiring the minimum skill levels that lead them to skilled jobs. Hence, those males (females) with ability level $a \geqslant a_M$ ($a \geqslant a_F$) will invest to acquire the minimum levels of skill required by employers for a skilled position.

Let $G(a)$ denote the cumulative distribution of ability. Define $\beta_M = 1 - G(a_M)$ and $\beta_F = 1-G(a_F)$ as the proportions of males and females who decide to obtain the minimum levels of skills required for skilled jobs. Let

$$S_s = T\alpha\beta_M + T(1-\alpha)\beta_F \tag{43}$$

represent the supply of skilled labour to the market. Since the equilibrium market wage for unskilled is given by the fixed reservation wage (i.e. $w_u^* = \overline{w_r}$), the equalisation of equations (35) and (43) (i.e. $N_s = S_s$) gives the equilibrium market wage differential between skilled and unskilled labour: $w_s^* - w_u^*$. Thus, we can define the marginal male and female that acquire the minimum levels of skills in equilibrium respectively by a_M^* and a_F^*. Those workers that do not obtain skilled positions are either in unskilled jobs or unemployed. We assume that those males that do not hold skilled positions are randomly distributed between unemployment and unskilled jobs. The same assumption applies to females that are not in skilled positions.

From assumptions (37), (38), (39), (40), and the fact that $\overline{e_M} < \overline{e_F}$, we have that the ability level of the marginal female should be higher than that of the marginal male, that is,

$$a_F^* > a_M^*. \tag{44}$$

To see why this is so Figure 2 depicts a possible cost function as the skill level varies for different ability levels.[30] The ability levels $\underline{a}$ and $\overline{a}$ denote respectively the lowest and highest possible levels of the support of the ability distribution. The equilibrium wage differential $w_s^* - w_u^*$ is the marked on the vertical axis. Given that $\overline{e_M} < \overline{e_F}$ and assumptions (38) and (40), the cost function associated with a_M^* must lie everywhere above the one associated with a_F^*, thus $a_M^* < a_F^*$.

Let $\beta_M^* = 1-G(a_M^*)$ and $\beta_F^* = 1-G(a_F^*)$ denote respectively the proportions of males and females who obtain skilled jobs in equilibrium. Now, since $a_M^* < a_F^*$, we have the result that

$$\beta_M^* > \beta_F^*, \tag{45}$$

so the proportion of males who hold skilled jobs is higher than the proportion of females in this type of jobs.[31] Note, however, that the average ability and the average skill level of those women that obtain skilled jobs will be higher than the corresponding averages for males in skilled positions.

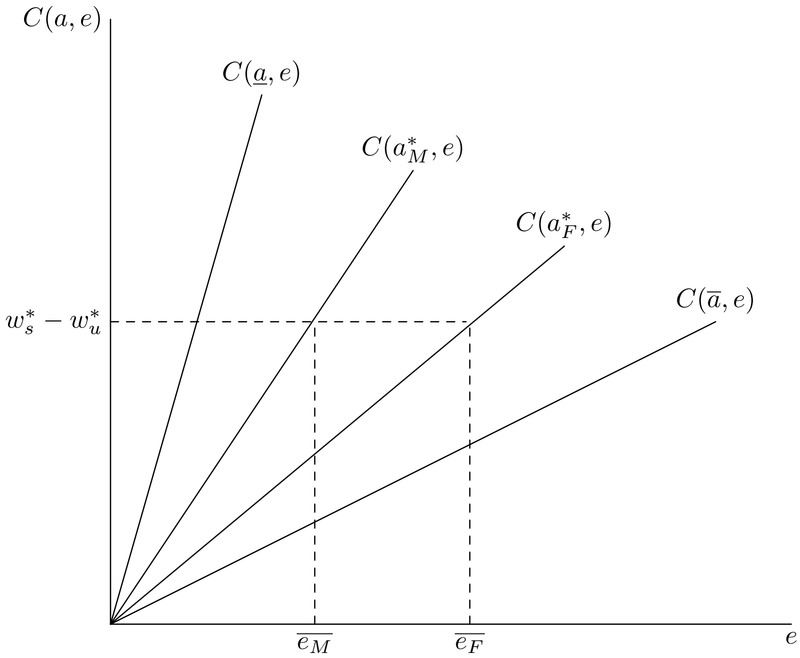
We now turn to the quality sorting part of the model. Recall that firms are heterogeneous in their relative demand for skilled workers.[32] Let q_j be the share of firm j's labour

[30] Note that the depicted cost function respects assumptions (37), (38), (39), and (40). We have depicted it in a linear fashion for simplicity.

[31] More formally, we are saying that $\beta_M^* = Pr(S|M) > Pr(S|F) = \beta_F^*$, where Pr denotes proportion and S skilled jobs.

[32] This relative demand is essentially determined by the technological parameters s_j and u_j.

Figure 2: Cost Function for Different Ability Levels



force that is skilled. Let H_j and h_j denote firm j's fraction of males that are hired for skilled and unskilled jobs respectively. Noting that males and females that hold skilled jobs produce the same output, every firm is indifferent between hiring a male or a female for skilled positions (provided that $\overline{e_F} > \overline{e_M}$).[33] This also applies to males and females in unskilled positions. Therefore, we have that both H_j and h_j will be constant across firms and given respectively by

$$H = \frac{\alpha\beta_M^*}{\alpha\beta_M^* + (1-\alpha)\beta_F^*} \tag{46}$$

and

$$h = \frac{\alpha(1-\beta_M^*)}{\alpha(1-\beta_M^*) + (1-\alpha)(1-\beta_F^*)}. \tag{47}$$

One important result is that the proportion of males in skilled jobs is higher than the proportion of males in unskilled jobs, that is, $H > h$. To prove this let $k = \frac{\frac{H}{1-H}}{\frac{h}{1-h}} = \frac{\frac{\beta_M^*}{\beta_F^*}}{\frac{(1-\beta_M^*)}{(1-\beta_F^*)}}$. From the previous part of the model we obtained the result that $\beta_M^* > \beta_F^*$, so k is clearly greater than unity. It follows then that $\frac{H}{1-H} > \frac{h}{1-h}$, thus $H > h$.

The proportion of females in firm j is given by

$$F_j = q_j(1-H) + (1-q_j)(1-h) = (1-h) - q_j(H-h). \tag{48}$$

Since $H > h$ we obtain the result that the larger the fraction of firm j's labour force that is skilled the lower the proportion of females in the firm, that is

$$\frac{\partial F_j}{\partial q_j} = -(H-h) < 0. \tag{49}$$

[33] In other words, the employer is indifferent between hiring a proportion β_M of males or β_F of females. Note that in this model the employer does not have discriminatory tastes either against females or in favour of males.

Obviously, the opposite result applies for the proportion of males in the firm ($M_j = h + q_j(H - h)$). Hence, we conclude that there will be sorting of males and females across firms: those firms with higher proportions of skilled (unskilled) jobs will hire relatively more males (females) for those jobs.

The average wage of males and females in firm j is given respectively by

$$\begin{aligned} w_j^M &= \frac{q_j H w_s^* + (1 - q_j) h w_u^*}{q_j H + (1 - q_j) h} \\ &= \frac{q_j [H w_s^* - h w_u^*] + h w_u^*}{q_j (H - h) + h} \end{aligned} \tag{50}$$

and

$$\begin{aligned} w_j^F &= \frac{q_j (1 - H) w_s^* + (1 - q_j)(1 - h) w_u^*}{q_j (1 - H) + (1 - q_j)(1 - h)} \\ &= \frac{q_j [(1 - H) w_s^* - (1 - h) w_u^*] + (1 - h) w_u^*}{q_j (h - H) + (1 - h)}. \end{aligned} \tag{51}$$

Now, taking the derivatives of equations (50) and (51) with respect to q_j we obtain

$$\frac{\partial w_j^M}{\partial q_j} = \frac{Hh(w_s^* - w_u^*)}{[q_j(H - h) + h]^2} > 0 \tag{52}$$

and

$$\frac{\partial w_j^F}{\partial q_j} = \frac{(1 - H)(1 - h)(w_s^* - w_u^*)}{[q_j(h - H) + (1 - h)]^2} > 0, \tag{53}$$

so the average wages of males and females are positively related to the fraction of skilled jobs in firm j.[34]

From results (49), (52), and (53) we have then that the higher (smaller) the fraction of firm j's labour force that is skilled (i.e. the higher (smaller) q_j): (1) the smaller (higher) the proportion of females in the firm; and (2) the higher (smaller) the average wages of males and females in this firm. Thus, the model predicts the existence of a negative correlation between the proportion of females in the firm and the average wages of the two gender groups. This negative relationship between the feminisation degree of firms and the wages of males and females has also been predicted by the monopsonistic model presented in the previous section (see case C in Table 2).

4 Data

4.1 Description

The data source we use in our the empirical work is the "Relação Anual de Informações Sociais" (RAIS) – Annual Social Information Report. It is a large scale administrative database that contains matched employer-employee information collected by the Brazilian federal government. The data are based on compulsory reports that are sent annually to the central government by all registered employers in the country.

The data set contains information on every single labour contract the employer had with his/her employees in a particular calendar year. More specifically, each observation

[34] Note that since workers compare the cost of acquiring skills with the skilled-unskilled wage differential we must have that $w_s^* - w_u^* > 0$.

corresponds to a unique worker-establishment combination, with unique identifiers for the employee and the establishment. For each observation, there is information on the individual's sex, age, schooling level, tenure, occupation, contractual hours, and monthly wages. In addition, the industry and municipality where the establishment is located are also informed.

The information on workers' wage is used by the federal government to implement a long-standing social programme in Brazil, the so-called "Abono Salarial" (Wage Bonus).[35] Given that individual workers are the beneficiaries of the programme, employers ought to be careful in providing the wage information to the government. As a result, one may expect to find little measurement error in the wage variables.

We were able to obtain data from RAIS for three consecutive years: 2000, 2001, and 2002. Using the worker and establishment identifiers we were thus able to construct a panel of linked employer-employee data. It is important to point out that RAIS gathers information only for registered workers and establishments. Hence, if workers are out of the registered (formal) sector in a particular year (e.g. in informal jobs or self-employment), information about them is not present in RAIS of that year. Similarly, when entire establishments move into informality, it is unlikely that their employees' information will be present in RAIS. Hence, there are individuals and establishments that are not continuously observed over the three years period, so the resulting data set is an unbalanced panel.[36]

The data set for the whole country contains approximately 60 million observations. Due to the huge size of the data set, and because we wanted to investigate the relationship between establishment sex segregation and wages in local labour markets, the empirical analysis is based on the data available for one medium sized municipality of Brazil, namely Belo Horizonte. This city is the capital of Minas Gerais – which is one of the most important states in Brazil –, and is considered to be representative of the urban labour markets in the country. Even for this municipality alone, the initial data set contained 3,705,602 observations.

4.2 Wage Variable

RAIS contains information on wages for every month the individual worked at the establishment. The information on the individual's wage is the overall monthly compensation, that is, the sum of the contractual wage plus several other pecuniary components such as overtime pay, bonuses, tips, and the like. By Brazilian laws, every employer has to pay once a year to each of his/her employees what is called the "thirteenth wage". This payment is equal to the contractual wage only, and its value is proportional to the length of the worker's labour contract during the year. For instance, if the employee worked for three months at a specific establishment, he/she is paid by the employer an additional wage payment corresponding to one fourth of his/her contractual wage.

Given that men tend to work more overtime hours than women, the use of the overall compensation of the workers is not warranted. For example, it could be that the overall compensation of males is higher than that of females simply because the former group works longer hours than the latter one. This may also apply to the other components of the overall compensation that is reported in RAIS. Hence, a more comparable measure of the wages of the two gender groups should exclude overtime pay and other compensation components that may be different between the two groups. The information on the 13$^{\text{th}}$ wage of workers

[35] Workers who are paid on average less than two minimum wages are entitled to receive a yearly wage bonus through this programme.

[36] This also happens because some establishments are born and die every year.

is one such a measure, and for this reason the wage variable we use in the empirical analysis is based on it. More specifically, we constructed the wage variable through some steps. Firstly, because many individuals worked only a fraction of the year in the establishment, we converted their 13^{th} wage information into a monthly figure. For that, we created a converting factor using the worker's employment spell in the establishment in number of months, e (i.e. factor $= 12/e$). Secondly, using the information on the number of contractual weekly hours we calculated the contractual hourly wage for each observation by dividing the constructed monthly wage by the number of weekly hours times four. Our final wage variable is the logarithm of the real contractual hourly wage, where we used the National Consumer Price Index (INPC) to deflate the contractual hourly wage figures.

4.3 Construction of Covariates

The schooling level of workers is reported as the highest completed grade. However, some levels are reported in bracketed categories: 0 (illiterate), 1 to 3 years, 4 years, 5 to 7 years, 8 years (complete primary education), 9 to 10 years, 11 years (complete high school), 12 to 14 years, and over 15 years (at least college degree). For those individuals in non-single categories we used the midpoint of the category years as their schooling level (i.e. 2 years for the 1-3 category, 6 years for the 5-7 category, 9.5 years for the 9-10 years, 13 years for the 12-14 category). The only exception was the last category, for which we fixed the schooling level at 15 years.

We used potential experience (age - schooling - 6) to measure total labour market experience of workers. RAIS also contains information on the tenure of the workers in the establishment. This variable is measured in months with two decimal digits.

The occupations of workers were grouped into five categories: blue-collars, clerical, professionals, managers, and miscellaneous occupations. The industry to which the establishment belongs were also divided into five categories: agriculture, manufacturing, construction, trade, and services.

The measure of establishment sex segregation we use is the proportion of females in the establishment's workforce. This was calculated for each pair establishment-year, so there is variation on both dimensions. We also calculated a measure of establishment size, which was defined as the total number of employees that each establishment had in each year.

4.4 Observation Selection

As we saw in section 3 most theories that aim to explain the existence of a gender wage gap are based on profit-maximising behaviour of firms. For that reason, we excluded observations corresponding to not-for-profit establishments, including the public sector. We also deleted observations from all establishments that reported having no employees.[37] Altogether these exclusions reduced the data set to 2,412,704 observations. It was for this resulting data set that we calculated all variables at the establishment level, such as the its proportion of females and its employment size.

Some individuals in the data set had more than one job in the same months within a year. In order not to contaminate estimation with information on secondary labour market activities of individuals, we selected the observations that corresponded to the main job of the individual. We implemented that by selecting the observations for which the wage

[37] This basically happens because many self-employed workers register their own firms in order to pay less taxes.

and hours of work were the largest for each individual in this group (data set reduced to 2,316,838 observations).

We imposed some other filters to the data. First, we deleted the observations for the individuals who were younger than 25 or older than 65 at the date of their first appearance in the data set. Second, we only kept those workers that were in the same occupation over time. Presumably, those are the workers with higher labour market attachment. Third, since the municipality of Belo Horizonte belongs to a metropolitan area we excluded all observations corresponding to the agriculture industry. Finally, because the construction industry is an outlier in terms of the proportion of women it has (less than 4%), we also did not include the observations from this industry. There remained 885,637 observations after imposing these filters.

In the empirical analysis we work with two distinct data sets. The first contains only those workers that remained at the same establishment across the years (hereafter non-movers file). The non-movers file has 796,604 observations, out of which 487,861 (61.2%) refer to males and 308,743 (38.8%) to females. The second contains all workers, including those that moved across establishments over time (hereafter all-workers file). Out of the 885,637 observations of the complete file, 544,051 (61.4%) are for males and 341,586 (38.6%) for females.

4.5 Descriptive Statistics

Table 3 provides descriptive statistics for the two data sets we use in estimation. Rows 1 and 2 report the average (log) hourly wage for men and women for both data sets. These rows show that there is a substantial wage gap between the two sex groups: in terms of geometric (arithmetic) means, the average wage of all males is 39.1% (41.2%) higher than that of all females, and 41.9% (43.9%) when only non-movers are considered. Row 3 presents the average hourly wage for workers in the manufacturing industry. The female/male wage ratio in this industry may be compared to the available evidence for a set of 58 countries (see International Labour Office (2003, Table 5g)). The unweighted average of this ratio for this set of countries is 77.2%, whereas for Brazil this figure is around 50%, indicating that the relative wage of women in Brazil tends to be lower than in other countries, at least for the manufacturing sector.[38] It is important to notice that the average wage figures presented in rows 1 to 3 are very similar between the two data sets.

Rows 4 to 6 report the average experience, tenure, and schooling of workers. Males have, on average, longer experience and tenure than females. This latter group has, however, half-year higher average schooling than the former group. Together, these figures indicate that there are important differences in productivity-related characteristics between the two gender groups. Again, we note that the comparison between the two data sets shows very similar figures.

Row 7 presents the average female proportion across establishments. Males tend to work in establishments where females represent around one fourth of the establishments' labour force. In contrast, females typically work in establishments where the proportion of females is around three fifths of the establishments' workforce. Thus, females tend to work in predominantly female establishments, with the opposite being valid for males. When taking both sexes together (not shown) the average female proportion is 37.3% for the all-workers data set, and 37.1% for non-mover workers, so the difference between the

[38] It should be noted, however, that these figures are not strictly comparable, since the coverage, definitions and methods of calculating wage statistics differ significantly from country to country.

Table 3: Descriptive Statistics: Municipality of Belo Horizonte

	All Workers		Non-Movers	
	Males	Females	Males	Females
1. Log Hourly Wage	1.30	0.97	1.35	1.00
	(0.001)	(0.002)	(0.001)	(0.002)
2. Hourly Wage	6.38	4.52	6.56	4.56
	(0.02)	(0.02)	(0.02)	(0.02)
3. Hourly Wage in Manufacturing	7.20	3.58	7.33	3.65
	(0.08)	(0.03)	(0.08)	(0.03)
4. Experience	23.2	22.2	23.2	22.2
	(0.01)	(0.02)	(0.01)	(0.02)
5. Tenure	58.4	48.0	62.8	50.9
	(0.1)	(0.1)	(0.1)	(0.1)
6. Schooling	8.2	8.7	8.3	8.8
	(0.005)	(0.006)	(0.005)	(0.006)
7. Female Proportion	0.25	0.58	0.24	0.58
	(0.0003)	(0.0004)	(0.0003)	(0.0004)
8. Establishment Size	1270	858	1334	863
	(3.7)	(3.3)	(4.0)	(3.6)
9. Occupation				
9a. Blue-Collar	0.70	0.57	0.68	0.56
	(0.0006)	(0.0008)	(0.0007)	(0.0009)
9b. Clerical	0.12	0.28	0.13	0.28
	(0.0004)	(0.0008)	(0.0005)	(0.0008)
9c. Professional	0.11	0.09	0.11	0.10
	(0.0004)	(0.0005)	(0.0004)	(0.0005)
9d. Managerial	0.08	0.06	0.08	0.06
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
10. Industry				
10a. Manufacture	0.13	0.11	0.13	0.12
	(0.0005)	(0.0005)	(0.0005)	(0.0006)
10b. Trade	0.21	0.21	0.21	0.21
	(0.0006)	(0.0007)	(0.0006)	(0.0007)
10c. Services	0.66	0.67	0.66	0.67
	(0.0006)	(0.0008)	(0.0007)	(0.0008)
Observations	544051	341586	487861	308743
Number of workers	211284	131001	193477	124194
Number of establishments	19321	17573	15987	14841

Notes:.
(1) Standard errors in parentheses.
(2) The hourly wage is in Brazilian monetary units (Reais, R$). It has been deflated by the National Consumer Price Index (INPC, base year 2002).
(3) Experience and schooling are measured in years. Tenure is measured in months. Establishment size is the average number of employees across establishments. Female proportion is the average proportion of females across establishments. Part-time is the proportion of individuals working less than 30 hours per week. All figures in the table refer to the period 2000-2002.

two data sets is again very small. Row 8, which reports the average number of employees across establishments, shows that males work in larger establishments than females, with the relative difference being around 48% when all workers are considered, and 55% for non-movers workers only.

The rows 9a to 9d present the occupational composition for males and females. These rows show that males and females are concentrated in blue-collar occupations, and that the proportion of females in clerical occupations is relatively higher than that of males.

They also show that a slightly larger fraction of males are in professional and managerial occupations relatively to females. Finally, the rows below row 10 present the industrial composition for the two sexes. They show that the distribution of the two groups is similar across the industries. Note again that there are very small differences in the occupational and industrial compositions between the sexes for the two data sets we use in estimation.

5 Measuring Interplant Sex Segregation

This section is dedicated to measuring the magnitude sex segregation across establishments. To evaluate interplant segregation patterns we employ two commonly used indices, namely the Duncan dissimilarity index (D) and the Gini coefficient of segregation (G). Both measures are bounded between zero and unity. For instance, a value of zero corresponds to complete evenness, a case that occurs when every plant's proportion of females is equal to the proportion of females in the labour force. In contrast, a value of one represents complete unevenness, a case in which every plant's employees are either all male or all female. More specifically, let m_j and f_j denote respectively establishment j's share of male and female employees in the data, where $j = 1, ..., J$. Then the Duncan dissimilarity index is simply

$$D = \frac{1}{2} \sum_{j=1}^{J} |f_j - m_j|. \tag{54}$$

This index has the simple interpretation of the share of females (or males) that would have to change establishments so as to make the data completely even. The the dissimilarity index has been criticised on the ground that it is equally sensitive to small and large departures from evenness (see Hutchens (2001)). The Gini coefficient of segregation has been suggested instead, being defined as

$$G = 1 - \sum_{j=1}^{J} f_j \left(m_j + 2 \sum_{i=j+1}^{J} m_i \right), \tag{55}$$

where it is assumed that the data have been firstly sorted by the ratio f_j/m_j.[39]

As pointed out by Carrington and Troske (1997), one unattractive feature of these traditional indices of segregation is that both measures display positive values even if males and females are randomly distributed across establishments. Carrington and Troske (1997) show that this problem depends essentially on two factors, namely the distribution of establishment sizes and the share of females within each establishment size class. More importantly, they show that as the fraction of small plants in the sample increases random allocation of workers will be associated with higher values of the segregation measures.[40]

[39] The difference between D and G can be seen using the example given in Carrington and Troske (1998, p. 450). Suppose there is a four-plant sample whose male/female distribution is as follows: each of plants 1 and 2 employs 50 females and 50 males, plant 3 has 75 females and 25 males, and plant 4 has 25 females and 75 males. For this case, $D = 0.25$ and $G = 0.375$, characterising this distribution as segregated. Now, suppose that one wants to increase sex segregation through two distinct swaps of males and females across the plants: (a) plants 1 and 2 swap a male for a female, or (b) plant 3 trade a male to plant 4 in return for a female. For both cases (a) and (b) the dissimilarity index displays the same value ($D = 0.26$), while the Gini coefficient would be respectively 0.38 and 0.39. Thus, the dissimilarity index treats the two cases symmetrically, whereas the Gini coefficient puts more weight on the tails of the interplant gender distribution treating case (b) as the one generating the highest increase in segregation.

[40] For example, the dissimilarity index can be seen as a weighted average of within-size class segregation, plus some terms that account for unevenness across size classes. Hence, in cases for which small plants constitute a large size-weighted fraction of the sample random segregation will be high.

Given that our data contain a large number of small establishments, we quantify these two segregation measures following the procedures proposed by Carrington and Troske (1997).[41] The idea is to separate the part of segregation that can be attributed to the random allocation of workers across plants from the part that is due to systematic segregation.

More specifically, let the Duncan and the Gini indices of random segregation be respectively denoted by D^* and G^*. They are the indices that would be computed from data in which workers from both sexes are allocated to establishments by pure chance. To compute those indices we consider the empirical distribution of sexes in the population across different establishment sizes, and randomly allocate the workers according to this empirical distribution. This procedure maintains the original structure of the data set both in terms of the distribution of establishment sizes and the gender composition of the labour force. The procedure is repeated 100 times with each replication containing a different random sample of 10% of establishments. In each replication the dissimilarity index and the Gini coefficient are calculated using the same formulas as presented above ((54) and (55)). The indices D^* and G^* are the average of the calculated indices across all replications.

The random indices D^* and G^* are then used to obtain two measures of systematic segregation, denoted respectively $\hat{D}$ and $\hat{G}$. Those measures are intended to transform the original indices into segregation measures that control for the role of random assignment in generating unevenness. They are defined as (Carrington and Troske (1997, p. 406))

$$\hat{S} = \begin{cases} \frac{S-S^*}{1-S^*} & \text{if } S \geq S^* \\ \\ \frac{S-S^*}{S^*} & \text{if } S < S^* \end{cases} \tag{56}$$

where $\hat{S} = \hat{D}, \hat{G}$ and $S^* = D^*, G^*$. The interpretation of these measures of systematic segregation is simple. If actual segregation exceeds random segregation (i.e. $S > S^*$), then $\hat{S} > 0$ quantifies the excess segregation over what would be expected by chance ($S - S^*$), expressed in terms of the maximum amount of such excess segregation that could possibly occur ($1 - S^*$). Note that $\hat{S} = 1$ corresponds to the case of complete unevenness (i.e. $S = 1$), but $\hat{S} = 0$ is equivalent to random allocation (i.e. $S = S^*$). When there is excess evenness (i.e. $S < S^*$), then $\hat{S} < 0$ is simply excess evenness over what would be dictated by chance ($S - S^*$), expressed as the maximum amount of such excess evenness that could possibly occur (S^*). The case where $\hat{S} = -1$ corresponds to the situation of complete evenness (i.e. $S = 0$).

In sum, the systematic segregation measures are a simple re-mapping of the original values of D and G from the $[0, 1]$ interval into the $[-1, 1]$ interval, where the segment $[0, 1]$ ($[-1, 0]$) corresponds to the case of excess unevenness (evenness) in the sense that total segregation exceeds (is less than) random segregation. One advantage of measuring systematic segregation is that it can be used to compare the amount of segregation across different samples.[42]

Table 4 reports the three measures of segregation (total, random, and systematic) for both the dissimilarity index and the Gini coefficient.[43] The rows below number 1 present

[41] The proportion of establishments with less than 10 employees is 16.6%, with less than 50 employees is 44.4%, and with less than 100 employees is 54.1%.

[42] Clearly, unless random unevenness is constant across samples, the comparison of actual segregation indices from any two samples can give wrong conclusion about which sample is more segregated.

[43] Standard-errors of the indices are calculated from bootstrap techniques as proposed by Carrington and Troske (1997).

Table 4: Measures of Interplant Sex Segregation: Municipality of Belo Horizonte

	Dissimilarity Index			Gini Coefficient		
	Total (D)	Random (D^*)	Systematic ($\hat{D}$)	Total (G)	Random (G^*)	Systematic ($\hat{G}$)
1. All Workers						
1a. Year 2000	0.496	0.154	0.404	0.702	0.517	0.382
	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)
1b. Year 2001	0.496	0.168	0.394	0.703	0.514	0.389
	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)
1c. Year 2002	0.482	0.166	0.379	0.701	0.521	0.375
	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)
2. Industry (2000)						
2a. Manufacture	0.547	0.216	0.421	0.691	0.471	0.415
	(0.003)	(0.001)	(0.005)	(0.001)	(0.001)	(0.002)
2b. Trade	0.499	0.270	0.313	0.650	0.527	0.259
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
2c. Services	0.474	0.133	0.393	0.741	0.527	0.452
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)

Notes:.
(1) Bootstrap standard errors in parentheses.
(2) See text for description of how these measures are obtained.

results separately for each year available in our data set. Both traditional measures of segregation (D and G) show that interplant gender segregation is substantial and relatively stable over the years. As the random measures of these indices reveal (D^* and G^*), a considerable part of total segregation could be attributed to random allocation of workers across establishments. Since the random measures are less than the standard measures, systematic segregation is positive for all years. This implies that there is excess unevenness as compared to the maximum segregation that could be expected from a random distribution of workers across plants. Thus, we may conclude that men and women are systematically segregated in the (registered) Brazilian labour market. It is interesting to note that systematic segregation seems to be lower in Brazil than in Portugal, where the corresponding figures are $\hat{D} = 0.49$ and $\hat{G} = 0.67$ (Vieira et al. (2003, Table 1)).

The rows of below number 2 report the same segregation measures from stratified data by industry for the year 2000. The figures reveal that segregation within industries is not substantially different from what is observed for the labour market as a whole. This implies that only a small part of the aggregate segregation can be ascribed to inter-industry segregation. The figures for the manufacturing industry can be compared to those of the US manufacturing as reported by Carrington and Troske (1998, Table 2). Overall, it seems that systematic segregation in the Brazilian manufacturing industry is higher than that of its US counterpart: the systematic dissimilarity index for the former country is higher than that for the latter ($\hat{D} = 0.33$), and the systematic Gini coefficient is of similar magnitude ($\hat{G} = 0.45$).

In sum, the evidence presented in Table 4 indicates that the distribution of the sexes across establishments is quite uneven. Part of this unevenness, however, is consistent with random allocation of workers across establishments. Nevertheless, the results suggest that the systematic component is also quite substantial, representing an important part of the segregation patterns observed in the (registered) Brazilian labour market.

6 Empirical Methodology

The phenomenon we are trying to study refers to how the wages of males and females vary with the feminisation degree of a firm. Clearly, the wages of workers depend on a large set of factors, some of which are observed (or at least can be proxied) and some of which are not (at least by the econometrician). Among the latter set of factors, there are two that seem to play major roles. The first is workers' unobserved traits such as ability, motivation, and preferences. The second, which is many times neglected in wage studies, is firms' unobserved characteristics, such as (management) efficiency and preferences (in particular discriminatory tastes). All these unobserved components may play a substantial role in explaining wage heterogeneity across individuals and firms. In addition, these unmeasured characteristics of workers and firms may be correlated with the observed covariates included in wage regressions, and in particular with our variable of interest, the proportion of females in a plant. For instance, it could be that individuals with lower unmeasured ability are sorted into plants that have a predominantly female labour force. It could also be that employers with stronger discriminatory tastes hire relatively less women in their workforces. Ideally then, one would want to control for these unobserved specific factors so that it becomes possible to evaluate their influence on the estimates of the parameters of interest.

One of the most used and powerful ways to deal with the presence of unobserved specific components in the model is the availability of panel data and the use of longitudinal methods. Indeed, one of the major advantages of having panel data is that the analyst can employ longitudinal methods to deal with unobserved specific terms. In our case, the availability of a panel of matched employer-employee data allows us to incorporate such potentially important components in the model, namely a worker- and an establishment-specific effect. To the best of our knowledge, this is the first study that does that to investigate the connection between gender wages and the feminisation degree of firms.

To that extent, we use a dynamic panel data model, which is our most general model. In section 8 we conduct several robustness checks in which some other models are used. Consider the following wage equation

$$y_{ijt} = x_{1it}\beta_1 + x_{2i}\beta_2 + z_{1jt}\gamma_1 + z_{2j}\gamma_2 + \theta_i^* + \phi_j^* + \varepsilon_{ijt} \tag{57}$$

$$\varepsilon_{ijt} = \rho\varepsilon_{ij,t-1} + \upsilon_{ijt}, \tag{58}$$

where y_{ijt} is the log wage of individual $i = 1, ..., N$ in year $t = 1, ..., T$ at establishment $j = 1, ..., J$, x_{1it} and x_{2i} represent respectively time-variant and time-invariant characteristics of individual i, z_{1jt} and z_{2j} stand for time-variant and time-invariant characteristics of establishment j, and θ_i^* and ϕ_j^* denote respectively unmeasured, time-invariant person- and establishment-specific effects. The term ε_{ijt} is a disturbance term that is assumed to follow an AR(1) process, with $|\rho| < 1$, and υ_{ijt} is an mean zero error term that is not correlated across workers, establishments and time periods but whose variance may be clustered within establishments.

The variables included in x_{1it} are the workers' experience, experience squared and tenure in the establishment, and the workers' schooling level and occupational group are the time-invariant variables included in x_{2i}. The variables establishment female proportion and establishment size are the variables in z_{1jt}, and z_{2j} contains the industry of the establishment. We also include year dummies in all specifications.

Combining equations (57) and (58) we can obtain a 'common factor' form

$$\begin{aligned}
y_{ijt} &= \rho y_{ij,t-1} + x_{1it}\beta_1 - x_{1i,t-1}\beta_1\rho + x_{2i}\beta_2(1-\rho) + z_{1jt}\gamma_1 - z_{1j,t-1}\gamma_1\rho + \\
&\quad + z_{2j}\gamma_2(1-\rho) + \theta_i^*(1-\rho) + \phi_j^*(1-\rho) + \upsilon_{ijt} \\
&= \rho y_{ij,t-1} + x_{1it}\beta_1 + x_{1i,t-1}\pi_1 + x_{2i}\pi_2 + z_{1jt}\gamma_1 + z_{1j,t-1}\varphi_1 + \\
&\quad + z_{2j}\varphi_2 + \theta_i + \phi_j + \upsilon_{ijt}, \qquad (59)
\end{aligned}$$

where $\theta_i = \theta_i^*(1-\rho)$, $\phi_j = \phi_j^*(1-\rho)$, $\pi_1 = -\beta_1\rho$, $\pi_2 = \beta_2(1-\rho)$, $\varphi_1 = -\gamma_1\rho$, and $\varphi_2 = \gamma_2(1-\rho)$. Because of the presence of the lagged variables we loose one time period, so now $t = 2, ..., T$. It is assumed that υ_{ijt} is independently distributed with θ_i across i, and with ϕ_j across j. Let $w_{ijt} = (x_{1it}, z_{1jt})$. We assume that w_{ijt} may be correlated with the individual effects θ_i and ϕ_j, but that the first-difference Δw_{ijt} is not.

The presence of the individual effects θ_i and ϕ_j implies that they are necessarily correlated with the lagged dependent variable $y_{ij,t-1}$, and, under the above assumptions, also with w_{ijt}. Thus, the OLS estimator of the parameters is inconsistent. In addition, with small T - which is our case - the Within-Groups estimator is also inconsistent. The typical solution adopted in the panel data literature is to take first difference of the data in order to remove the unobserved specific terms.

However, it must be noted that the application of the first-difference transformation to equation (59) does not make both the individual effects to vanish when all workers are used. More specifically, when the data contain workers that move across establishments over time, the first difference of (59) will not remove ϕ_j for those workers.[44] One possible solution to this problem is to deal only with workers that remain at the same establishment over time. More formally, let $j = j(i, t)$ denote the establishment at which worker i was employed at period t. Hence, defining the workers that remained at the same establishment over time by the set *Non-Movers* $= \{i : j(i, t) = j(i, t-1), t = 2, ..., T\}$, the first-difference transformation is capable of eliminating the establishment-specific terms from equation (59). This set of workers constitutes our non-movers data set, and we shall use it to conduct estimation here. The idea of using non-mover workers to obtain consistent estimates of the regression parameters was proposed by Abowd et al. (1999).

Consider the first-difference transformation of the level equation (59) for non-mover workers[45]

$$\Delta y_{ijt} = \rho\Delta y_{ij,t-1} + \Delta x_{1it}\beta_1 + \Delta z_{1jt}\gamma_1 + \Delta z_{ij,t-1}\varphi_1 + \Delta\upsilon_{ijt} \qquad (60)$$

for $i = 1, ..., I^*$, $j = 1, ..., J^*$, and $t = 3, ..., T$, where the asterisk superscript denotes workers and establishments in the non-movers data set. Note that both the worker- and the establishment-specific effects have been removed. This also applies to the time-invariant variables in x_{2i} and z_{2j}.

Because $\Delta\upsilon_{ijt}$ is necessarily correlated with $\Delta y_{ij,t-1}$ (and potentially with the other terms), the OLS estimator of the parameters will be inconsistent. However, consistent estimates can be obtained through instrumental variable methods, with the fundamental

[44] For instance, suppose there are workers that moved from establishment j' to establishment j'' between two years. Then, the first difference of equation (59) will generate the term $(\phi_{j''} - \phi_{j'})$, therefore not removing the establishment-specific term.

[45] It should be noted that since estimation is based on non-mover workers the coefficients associated with tenure and its lag in equation 59 are not simultaneously identified in the presence of an intercept. Similar reasoning applies to the coefficients associated with experience and experience square and their lags. Hence, we do not include the term $x_{1i,t-1}$ in equation 59, which implies that its first difference is not present in the following equation.

requirements being that the instruments be correlated with the endogenous variables and orthogonal to Δv_{ijt}.

We assume that z_{1jt} is pre-determined in the sense that z_{1jt} and v_{ijt} are uncorrelated, but z_{1jt} may still be correlated with $v_{ij,t-1}$ and earlier shocks.[46]. This assumption implies that the term Δz_{1jt} is correlated with Δv_{ijt}, so together with $\Delta y_{ij,t-1}$ it also needs to be instrumented. The terms Δx_{1it} and $\Delta z_{1j,t-1}$ are not endogenous, so they can be used as instruments for themselves.

We assume that the initial conditions y_{ij1} and z_{1j1} are uncorrelated with subsequent disturbances v_{ijt} for $t = 2, ..., T$, that is, the initial conditions are pre-determined. Together with the assumption that v_{ijt} is serially uncorrelated, pre-determined initial conditions imply that $y_{ij,t-2}$ for $t = 3, ..., T$ are uncorrelated with Δv_{ijt}, so they can be used as instruments for $\Delta y_{ij,t-1}$ in the first-difference equation (60). Since $\Delta z_{1j,t-1} = z_{1j,t-1} - z_{1j,t-2}$ is already being used as instrument, we use $z_{1j,t-2}$ as instrument for Δz_{1jt}.

Estimation of the first-difference equation (60) is done through the Generalised Method of Moments (GMM) framework proposed by Arellano and Bond (1991). In implementing this procedure we allow for intra-establishment clustering.

Blundell and Bond (1998) and Blundell and Bond (2000) show that under some hypotheses about the initial condition process the properties of the first-differenced GMM estimator can be improved.[47] They propose a GMM estimator that combines the first-differenced equation with the level equation, where the endogenous variables in the latter equation are instrumented using appropriate time-differences of these variables.[48] They demonstrate that the performance of the standard GMM estimator of the first-difference AR(1) model can be substantially improved with this extended estimator, named system GMM. This is particularly important when the processes generating the variables in the model are close to random walks, in which case the variables in levels become weak instruments for their first-differences.

In sum, we estimate the model described by equations (59) and (60) using both the difference GMM and the system GMM approaches.[49] We implement the latter method in two flavours, namely the one-step and the two-step GMM procedures.[50] This is done separately for males and females and by sex and occupational group. Since there are only three time periods the model is exactly identified, so the usual tests of over-identifying restrictions (e.g. the Sargan test) and the $m1$ and $m2$ specification tests proposed by

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[46]That is

$$E[v_{ij,t+k}|z_{1jt}] \begin{cases} = 0 & \text{if } k \geq 0 \\ \neq 0 & \text{otherwise.} \end{cases}$$

[47]Consider the simple model $y_{it} = \rho y_{i,t-1} + \beta x_{it} + \eta_i + \epsilon_{it}$ and $x_{it} = \alpha x_{i,t-1} + \delta\eta_i + u_{it}$. By repeated substitution of the second equation in first-differences one obtains: $\Delta x_{it} = \alpha^{t-2}\Delta x_{i2} + \sum_{s=0}^{t-3} \alpha^s \Delta u_{i,t-s}$, so Δx_{it} will be uncorrelated with η_i if and only if Δx_{i2} is uncorrelated with η_i. The initial condition restriction $E\left[\left(x_{i1} - \frac{\delta\eta_i}{1-\alpha}\right)\delta\eta_i\right] = 0$ guarantees that $E[\Delta x_{i2}\eta_i] = 0$. Similarly one obtains that $\Delta y_{it} = \rho^{t-2}\Delta y_{i2} + \sum_{s=0}^{t-3} \rho^s(\beta\Delta x_{i,t-s} + \Delta\epsilon_{i,t-s})$, so Δy_{it} will be uncorrelated with η_i if and only if Δy_{i2} is uncorrelated with η_i. The initial condition restriction $E\left[\left(y_{i1} - \frac{\beta\frac{\delta\eta_i}{1-\alpha} + \eta_i}{1-\rho}\right)\eta_i\right] = 0$ guarantees that $E[\Delta y_{i2}\eta_i] = 0$. These two initial condition restrictions will be satisfied under mean stationarity of the x_{it} and y_{it} processes. See the cited papers for further discussion of these conditions.

[48]Arellano and Bover (1995) also proposed the use of lagged differences as instruments for equations in levels.

[49]Recall that we do not include the term $x_{1i,t-1}$ in equation (59). See footnote 45.

[50]When T=3 - which is our case here - the difference GMM is exactly identified, so there is no distinction between the one-step and the two-step estimates for this method. The two-step GMM uses a first-step consistent estimate of the parameters to construct the optimal weighting matrix that is used in the minimisation of the GMM objective function.

Arellano and Bond (1991) are not implemented. Notwithstanding, we report the common factor test for each parameter associated with the variables in $z_{1j,t-1}$, and the joint test for these parameters as a whole.

7 Results

7.1 By Sex

Table 5 reports the estimates obtained from the AR(1) model specified by equations (59) and (60). Columns (1) and (4) report the results from the difference GMM procedure for females and males respectively. Columns (2) and (5) display the results from the one-step system GMM, and columns (3) and (6) from the two-step system GMM for females and males respectively.

As it can be seen from this Table the estimates of the proportion female coefficient are negative and statistically significant at the 1% level for the system GMM models. The point estimates are still negative but not statistically different from zero for the difference GMM model, though.[51] Overall, these results indicate that if there is any effect of the feminisation degree of a firm on the wages of males and females, then this effect seems to be negative. It is interesting to note from the system GMM results that the wages of males tend to be more negatively affected by increases in establishment female proportion than the wages of females. This implies that this effect tends to reduce the gender wage gap.

The common factor tests do not reject the common factor restrictions for the difference GMM procedure but they do reject them for the system GMM models. This is indicative that the AR(1) may not be the correct specification. The lack additional time periods prevents the computation of other specifications tests (like the $m1$ or $m2$ tests) so that we could double-check whether there is in fact some type of misspecification of the error term in (58).

As for the other covariates, the results show that the size of the establishment has a small negative effect on wages of males and females. Potential experience increases the wages of both gender groups but at a decreasing rate.[52] The effect of tenure on wages is positive and of similar magnitude between the two gender groups. The effect of schooling has the expected positive sign, being slightly larger for males than for females. Working in the manufacturing industry (the excluded sector) tends to increase the wages of males, but this wage increment only appears for females in comparison with the trade sector. Working as a blue-collar (the excluded occupational group) tends to decrease the wages of both sexes. It is interesting to note that men tend to have higher wages in managerial occupations, while women in professional ones.

7.2 By Sex and Occupation

In this subsection we present the results for four different occupational groups (blue-collars, clerical, professional, and managerial) by sex. Obtaining results by occupational group is important since the effect of interest may differ across broad occupations. It could be, for instance, that the wage effect of establishment gender segregation is much stronger

[51] It is well known that the OLS estimator of the coefficient of lagged dependent variable is upward biased, whereas the Within-Groups estimator is downward biased. Although not shown in this and in the following tables, our OLS and Within-Groups estimates of this parameter corroborate this result.

[52] Since it is the age of individuals that changes potential experience over the years, the first difference of the potential experience variable plays the role of the intercept.

Table 5: AR(1) Model Estimates for Wage Equation by Sex

Covariates	Females			Males		
	DIF-GMM One-Step (1)	SYS-GMM One-Step (2)	SYS-GMM Two-Step (3)	DIF-GMM One-Step (4)	SYS-GMM One-Step (5)	SYS-GMM Two-Step (6)
$\log(\text{wage})_{t-1}$	0.1001*	0.1874***	0.3515***	0.0052	0.0728*	0.1691***
	(0.0543)	(0.0496)	(0.0456)	(0.0417)	(0.0389)	(0.0369)
Proportion female	-0.0886	-0.0891***	-0.1056***	-0.0267	-0.1975***	-0.2136***
	(0.2042)	(0.0247)	(0.0229)	(0.0372)	(0.0313)	(0.0271)
Proportion female_{t-1}	-0.0111	-0.1768***	-0.1150***	-0.0213	-0.1533***	-0.1039***
	(0.0463)	(0.0257)	(0.0235)	(0.0367)	(0.0279)	(0.0235)
Establishment size (1/10)	-0.0054***	-0.0004***	-0.0001**	-0.0067***	-0.0005***	-0.0000
	(0.0007)	(0.0000)	(0.0000)	(0.0004)	(0.0001)	(0.0000)
Establishment size_{t-1} (1/10)	0.0004***	0.0004***	0.0001	0.0002**	0.0008***	0.0002***
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Experience	-0.0299***	0.0082***	0.0066***	-0.0291***	0.0227***	0.0204***
	(0.0056)	(0.0009)	(0.0009)	(0.0052)	(0.0013)	(0.0012)
Experience square	-0.0001	-0.0001***	-0.0001***	-0.0001	-0.0003***	-0.0002***
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Tenure		0.0034***	0.0027***		0.0034***	0.0030***
		(0.0002)	(0.0002)		(0.0001)	(0.0001)
Schooling		0.0778***	0.0617***		0.0934***	0.0831***
		(0.0048)	(0.0045)		(0.0040)	(0.0038)
Trade		-0.1271***	-0.1063***		-0.2882***	-0.2599***
		(0.0085)	(0.0081)		(0.0127)	(0.0121)
Services		0.0052	0.0015		-0.0827***	-0.0798***
		(0.0051)	(0.0051)		(0.0053)	(0.0053)
Clerical		0.1589***	0.1288***		0.0861***	0.0778***
		(0.0100)	(0.0093)		(0.0060)	(0.0059)
Professionals		0.6510***	0.5246***		0.5337***	0.4810***
		(0.0396)	(0.0365)		(0.0231)	(0.0219)
Managers		0.4905***	0.3967***		0.5723***	0.5151***
		(0.0302)	(0.0281)		(0.0252)	(0.0241)
Intercept		-0.1359***	-0.0960***		-0.0379**	-0.0189
		(0.0166)	(0.0163)		(0.0130)	(0.0128)
Common factor tests: (P-value)						
Proportion female	0.7479	0.0000	0.0000	0.5604	0.0000	0.0000
Establishment size	0.6445	0.0000	0.3551	0.5914	0.0000	0.0000
All parameters	0.8825	0.0000	0.0000	0.7105	0.0000	0.0000
Number of Observations	60355	184549	184549	100907	294384	294384

Notes:
1. The dependent variable is the log of the real hourly wage.
2. Standard errors in parentheses.
3. Significance levels::10% **:5% ***:1%.*
4. All specifications include year dummies.
5. Common factor is a test of non-linear common factor restrictions. P-values are reported.
6. The instruments used for the endogenous variables are:
DIF-GMM: $log(wage)_{t-2}$, proportion $female_{t-2}$, establishment $size_{t-2}$
SYS-GMM: Diff. eqs. as DIF-GMM; Level eqs.: $\Delta log(wage)_{t-1}$, Δproportion $female_t$, and Δestablishment $size_t$.

in male-dominated occupations (e.g. blue-collar) than in occupations typically held by women (e.g. clerical).

Table 6 presents the results for blue-collar occupations. As in the overall sample case, only the estimates of the female proportion coefficient are negative and statistically significant for the system GMM procedure. It is interesting to note that the results for blue-collar occupations indicate that the negative effect of establishment sex segregation on wages is much larger for males than for females, meaning that it substantially reduces the gender wage gap within this occupational group. The common factor restrictions are not rejected

Table 6: AR(1) Model Estimates for Wage Equation by Sex: Blue-Collar Occupations

Covariates	Females			Males		
	DIF-GMM One-Step (1)	SYS-GMM One-Step (2)	SYS-GMM Two-Step (3)	DIF-GMM One-Step (4)	SYS-GMM One-Step (5)	SYS-GMM Two-Step (6)
$\log(\text{wage})_{t-1}$	0.1120***	0.0559	0.0483	0.0298	0.0215	0.0327
	(0.0470)	(0.0437)	(0.0409)	(0.0286)	(0.0276)	(0.0272)
Proportion female	-0.3065	-0.2239***	-0.2125***	-0.2437	-0.4916***	-0.4978***
	(0.2906)	(0.0399)	(0.0391)	(0.3631)	(0.0400)	(0.0399)
Proportion female$_{t-1}$	-0.0316	0.0121	0.0007	-0.0895	-0.1173***	-0.1119***
	(0.0594)	(0.0365)	(0.0362)	(0.0636)	(0.0348)	(0.0347)
Establishment size (1/10)	-0.0018*	0.0002***	0.0002***	-0.0041***	0.0006***	0.0008***
	(0.0007)	(0.0000)	(0.0000)	(0.0006)	(0.0001)	(0.0001)
Establishment size$_{t-1}$ (1/10)	-0.0001	-0.0001	-0.0001**	-0.0001	-0.0001	-0.0003***
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Experience	-0.0364***	-0.0021	-0.0017	-0.0269***	0.0181***	0.0181***
	(0.0079)	(0.0011)	(0.0011)	(0.0062)	(0.0011)	(0.0011)
Experience square	0.0000	0.0000*	0.0000	-0.0002	-0.0002***	-0.0002***
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Tenure		0.0030***	0.0031***		0.0034***	0.0034***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Schooling		0.0532***	0.0534***		0.0617***	0.0608***
		(0.0027)	(0.0025)		(0.0020)	(0.0020)
Trade		-0.0569***	-0.0573***		-0.2235***	-0.2220***
		(0.0070)	(0.0070)		(0.0085)	(0.0084)
Services		-0.0888***	-0.0916***		-0.1343***	-0.1355***
		(0.0071)	(0.0070)		(0.0062)	(0.0061)
Intercept		0.2942***	0.3038***		0.3548***	0.3623***
		(0.0240)	(0.0233)		(0.0180)	(0.0177)
Common factor tests: (P-value)						
Proportion female	0.4522	0.9906	0.7852	0.1844	0.0005	0.0004
Establishment size	0.0276	0.0958	0.0064	0.0706	0.1950	0.0001
All parameters	0.0633	0.2479	0.0234	0.1694	0.0005	0.0000
Number of Observations	32791	103056	103056	67245	199570	199570

Notes:
1. The dependent variable is the log of the real hourly wage.
2. Standard errors in parentheses.
3. Significance levels::10% **:5% ***:1%.*
4. All specifications include year dummies.
5. Common factor is a test of non-linear common factor restrictions. P-values are reported.
6. The instruments used for the endogenous variables are:
DIF-GMM: log(wage)$_{t-2}$, proportion female$_{t-2}$, establishment size$_{t-2}$
SYS-GMM: Diff. eqs. as DIF-GMM; Level eqs.: Δlog(wage)$_{t-1}$, Δproportion female$_t$, and Δestablishment size$_t$.

for the difference GMM estimates (marginally for females) and also for the one-step system GMM for females. As before, we may conclude that the effect of interest seems to be negative for both sexes.

Table 7 contains the results for clerical occupations. In the case of women's wages, the effect of working in a predominantly female establishment is negative and significant for both the difference and the system GMM methods. This is only observed for the difference GMM in the case of males. As in the overall sample case, the common factor restrictions are only accepted for the difference GMM method.

Table 8 displays the results for the professional occupational group. The effect of establishment female proportion is again negative and statistically significant for females for the three methods we employ. This effect is only significant for males in the case of the system GMM method. Differently from the previous cases, the effect of interest seems

Table 7: AR(1) Model Estimates for Wage Equation by Sex: Clerical Occupations

Covariates	Females			Males		
	DIF-GMM One-Step (1)	SYS-GMM One-Step (2)	SYS-GMM Two-Step (3)	DIF-GMM One-Step (4)	SYS-GMM One-Step (5)	SYS-GMM Two-Step (6)
$\log(\text{wage})_{t-1}$	0.3025***	0.3502***	0.3919***	0.1282	0.4760***	0.5450***
	(0.0681)	(0.0650)	(0.0642)	(0.0815)	(0.0889)	(0.0873)
Proportion female	-0.1467**	-0.3015***	-0.2641***	-0.2555***	-0.0506	-0.0310
	(0.0736)	(0.0562)	(0.0553)	(0.0774)	(0.0536)	(0.0453)
Proportion female_{t-1}	-0.0331	0.0111	-0.0046	-0.1697	0.0468	0.0216
	(0.0589)	(0.0498)	(0.0495)	(0.1149)	(0.0535)	(0.0458)
Establishment size (1/10)	-0.0055***	0.0004***	0.0004***	-0.0063***	0.0004***	0.0004***
	(0.0012)	(0.0001)	(0.0001)	(0.0017)	(0.0001)	(0.0001)
Establishment size_{t-1} (1/10)	0.0011***	-0.0005***	-0.0004***	0.0011**	-0.0004***	-0.0005***
	(0.0003)	(0.0001)	(0.0001)	(0.0004)	(0.0001)	(0.0001)
Experience	-0.0578***	0.0198***	0.0173***	-0.0482***	0.0198***	0.0165***
	(0.0112)	(0.0026)	(0.0026)	(0.0125)	(0.0041)	(0.0040)
Experience square	0.0005*	-0.0003***	-0.0003***	0.0002	-0.0003***	-0.0003***
	(0.0002)	(0.0000)	(0.0000)	(0.0003)	(0.0001)	(0.0001)
Tenure		0.0031***	0.0029***		0.0026***	0.0023***
		(0.0003)	(0.0003)		(0.0004)	(0.0004)
Schooling		0.0798***	0.0742***		0.0633***	0.0541***
		(0.0080)	(0.0079)		(0.0107)	(0.0104)
Trade		-0.1179***	-0.1140***		-0.1221***	-0.1098***
		(0.0151)	(0.0150)		(0.0243)	(0.0239)
Services		0.0693***	0.0625***		0.0201	0.0109
		(0.0138)	(0.0136)		(0.0123)	(0.0122)
Intercept		-0.3345***	-0.2872***		-0.3082***	-0.2328***
		(0.0462)	(0.0449)		(0.0611)	(0.0595)
Common factor tests: (P-value)						
Proportion female	0.2531	0.0040	0.0003	0.0748	0.4721	0.8506
Establishment size	0.1260	0.0000	0.0000	0.5935	0.0025	0.0014
All parameters	0.2007	0.0000	0.0000	0.1958	0.0103	0.0051
Number of Observations	17566	52450	52450	13060	37898	37898

Notes:
1. The dependent variable is the log of the real hourly wage.
2. Standard errors in parentheses.
3. Significance levels::10% **:5% ***:1%.*
4. All specifications include year dummies.
5. Common factor is a test of non-linear common factor restrictions. P-values are reported.
6. The instruments used for the endogenous variables are:
DIF-GMM: $log(wage)_{t-2}$, proportion $female_{t-2}$, establishment $size_{t-2}$
SYS-GMM: Diff. eqs. as DIF-GMM; Level eqs.: $\Delta log(wage)_{t-1}$, Δproportion $female_t$, and Δestablishment $size_t$.

to be more negative for females than for males, so here it increases the gender gap. The common factor tests do not reject the null for females (marginally for the two-step case), and for the one-step system GMM for males (also marginally).

Table 9 shows the results for managerial occupations. Interestingly, the effect of establishment female composition on the wages of females is statistically nil for all models we employ. So, working in plants with a predominantly female workforce does not seem to affect the wages of female managers. However, this effect seems to be negative for males managers, implying that establishment female segregation rises the gender wage differential for this type of occupation. The common factor restrictions are easily accepted in all methods for males, and in the difference GMM for females.

In sum, though some of the common factor tests reject the hypothesis that the AR(1) specification is correct, we may conclude from all results presented above that the wage

Table 8: AR(1) Model Estimates for Wage Equation by Sex: Professional Occupations

Covariates	Females			Males		
	DIF-GMM One-Step (1)	SYS-GMM One-Step (2)	SYS-GMM Two-Step (3)	DIF-GMM One-Step (4)	SYS-GMM One-Step (5)	SYS-GMM Two-Step (6)
$\log(\text{wage})_{t-1}$	0.0546	0.1107**	0.1327***	0.0921	-0.0082	0.0079
	(0.0528)	(0.0537)	(0.0527)	(0.0602)	(0.0572)	(0.0501)
Proportion female	-0.2603***	-0.4211***	-0.4928***	0.0177	-0.2167**	-0.3488***
	(0.1113)	(0.1562)	(0.1171)	(0.1067)	(0.0989)	(0.0977)
Proportion female$_{t-1}$	0.1923	-0.1773	-0.1043	0.3539**	0.1922*	0.3226***
	(0.1348)	(0.1466)	(0.1074)	(0.1152)	(0.0919)	(0.0905)
Establishment size (1/10)	-0.0103***	-0.0007	-0.0008	-0.0108***	0.0003	-0.0002
	(0.0013)	(0.0006)	(0.0004)	(0.0009)	(0.0002)	(0.0002)
Establishment size$_{t-1}$ (1/10)	0.0008	0.0006	0.0006	-0.0034**	-0.0001	0.0003*
	(0.0006)	(0.0006)	(0.0004)	(0.0013)	(0.0002)	(0.0002)
Experience	0.0056	0.0087**	0.0088**	-0.0486***	0.0266***	0.0242***
	(0.0151)	(0.0043)	(0.0041)	(0.0133)	(0.0034)	(0.0032)
Experience square	-0.0009*	0.0000	0.0000	0.0002	-0.0003***	-0.0002***
	(0.0004)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)
Tenure		0.0024***	0.0023***		0.0025***	0.0025***
		(0.0002)	(0.0002)		(0.0002)	(0.0001)
Schooling		0.1238***	0.1207***		0.1539***	0.1515***
		(0.0085)	(0.0085)		(0.0089)	(0.0078)
Trade		-0.2954***	-0.2850***		-0.5706***	-0.5409***
		(0.0367)	(0.0365)		(0.0420)	(0.0385)
Services		-0.0131	-0.0074		-0.1558***	-0.1533***
		(0.0259)	(0.0258)		(0.0172)	(0.0171)
Intercept		0.3281***	0.3281***		-0.0138	0.0056
		(0.0768)	(0.0738)		(0.0459)	(0.0445)
Common factor tests: (P-value)						
Proportion female	0.2002	0.0875	0.0726	0.0023	0.0416	0.0007
Establishment size	0.7664	0.3444	0.1591	0.0060	0.6064	0.0404
All parameters	0.4400	0.1507	0.0624	0.0001	0.0836	0.0013
Number of Observations	6353	17924	17924	12526	33292	33292

Notes:
1. The dependent variable is the log of the real hourly wage.
2. Standard errors in parentheses.
3. Significance levels::10% **:5% ***:1%.*
4. All specifications include year dummies.
5. Common factor is a test of non-linear common factor restrictions. P-values are reported.
6. The instruments used for the endogenous variables are:
DIF-GMM: $\log(wage)_{t-2}$, proportion female$_{t-2}$, establishment size$_{t-2}$
SYS-GMM: Diff. eqs. as DIF-GMM; Level eqs.: $\Delta \log(wage)_{t-1}$, Δproportion female$_t$, and Δestablishment size$_t$.

effect of working in predominantly female plants tends to be negative for females (except perhaps for female managers) and males. In what follows we implement several robustness checks so as to verify whether these conclusions are confirmed.

8 Robustness Checks

Our first robustness check was to run the dynamic model regressions excluding those establishments that were all-female or all-male. The result of this attempt did not produce important qualitative changes in the estimates reported in the previous section. Secondly, we have run the regressions excluding those establishments that had less than 10 employees in the first year of the data. Similar results were again obtained from this attempt. Finally, we have run the system GMM regressions with a balanced panel, but the results did not

Table 9: AR(1) Model Estimates for Wage Equation by Sex: Managerial Occupations

Covariates	Females			Males		
	DIF-GMM One-Step (1)	SYS-GMM One-Step (2)	SYS-GMM Two-Step (3)	DIF-GMM One-Step (4)	SYS-GMM One-Step (5)	SYS-GMM Two-Step (6)
$\log(\text{wage})_{t-1}$	-0.2930	-0.0832	0.1137	-0.3176	-0.1391	0.1216
	(0.3601)	(0.2967)	(0.1896)	(0.1866)	(0.1751)	(0.1375)
Proportion female	-0.0692	-0.1281	-0.0308	-0.2730**	-0.2994**	-0.1711*
	(0.5236)	(0.2300)	(0.1986)	(0.1240)	(0.1484)	(0.1024)
Proportion female$_{t-1}$	-0.4876**	-0.4431**	-0.4400***	-0.0187	0.1386	0.0667
	(0.2184)	(0.2107)	(0.1770)	(0.1325)	(0.1387)	(0.0928)
Establishment size (1/10)	-0.0141	0.0000	0.0001	-0.0110**	0.0005	0.0005***
	(0.0292)	(0.0003)	(0.0003)	(0.0037)	(0.0005)	(0.0001)
Establishment size$_{t-1}$ (1/10)	-0.0002	-0.0004	-0.0004	-0.0022**	-0.0002	-0.0002
	(0.0008)	(0.0002)	(0.0002)	(0.0007)	(0.0005)	(0.0001)
Experience	-0.0170	0.0124*	0.0094	-0.0260	0.0479***	0.0365***
	(0.0269)	(0.0066)	(0.0058)	(0.0216)	(0.0094)	(0.0079)
Experience square	-0.0004	-0.0001	-0.0001	-0.0006	-0.0005***	-0.0004***
	(0.0005)	(0.0001)	(0.0001)	(0.0004)	(0.0001)	(0.0001)
Tenure		0.0043***	0.0037***		0.0034***	0.0027***
		(0.0011)	(0.0007)		(0.0005)	(0.0004)
Schooling		0.1593***	0.1314***		0.2164***	0.1675***
		(0.0429)	(0.0279)		(0.0331)	(0.0262)
Trade		-0.0960*	-0.0758*		-0.4488***	-0.3468***
		(0.0435)	(0.0368)		(0.0756)	(0.0623)
Services		0.2672**	0.2169***		-0.1673***	-0.1335***
		(0.0816)	(0.0564)		(0.0339)	(0.0309)
Intercept		-0.1695	-0.1544		-0.7112***	-0.5675***
		(0.0926)	(0.0905)		(0.1286)	(0.1086)
Common factor tests: (P-value)						
Proportion female	0.0835	0.0496	0.0048	0.5985	0.2718	0.5822
Establishment size	0.7204	0.0991	0.0420	0.5833	0.6985	0.1386
All parameters	0.2226	0.0482	0.0039	0.7905	0.5174	0.2994
Number of Observations	3645	11119	11119	8076	23624	23624

Notes:
1. The dependent variable is the log of the real hourly wage.
2. Standard errors in parentheses.
3. Significance levels::10% **:5% ***:1%.*
4. All specifications include year dummies.
5. Common factor is a test of non-linear common factor restrictions. P-values are reported.
6. The instruments used for the endogenous variables are:
DIF-GMM: $\log(wage)_{t-2}$, proportion $female_{t-2}$, establishment $size_{t-2}$
SYS-GMM: Diff. eqs. as DIF-GMM; Level eqs.: $\Delta\log(wage)_{t-1}$, Δproportion $female_t$, and Δestablishment $size_t$.

change in a substantial way either.

Given these little changes in results when using the dynamic specification, we have implemented three other different empirical methods: within-groups, first-difference, and multilevel-mixed models. Though less general than the dynamic model, these methods are largely used, and can provide useful information to check the results we have obtained so far. We also implemented the multilevel method using the complete data set, that is, the data set that contains information not only for those workers that remained at the same establishment over time but for all workers. Finally, using a more general specification for the unobserved specific effects, we also applied the within-groups and first-difference procedures to the complete data set. We now report the results obtained from these strategies. We first present the results based on the non-movers sample, and then the results based on the all-workers data set.

8.1 Non-Mover Workers Results

8.1.1 Within-Groups and First-Difference

Consider the following equation

$$y_{ijt} = x_{1it}\beta_1 + x_{2i}\beta_2 + z_{1jt}\gamma_1 + z_{2j}\gamma_2 + \theta_i^* + \phi_j^* + \varepsilon_{ijt}, \tag{61}$$

which is identical to equation (57). Suppose now that ε_{ijt} is a disturbance term that is not correlated with any of the regressors in the equation, that is, assume that all covariates are strictly exogenous. As before, we allow its variance to be clustered within establishment units. Still using the data set with workers that remained at the same establishment over time, if we subtract each variable of equation (61) from their over-time mean we obtain

$$\widetilde{y}_{ijt} = \widetilde{x}_{1it}\beta_1 + \widetilde{z}_{1jt}\gamma_1 + \widetilde{\varepsilon}_{ijt}, \tag{62}$$

where the tilde notation denotes the original variable subtracted from its over-time mean (e.g $\widetilde{y}_{ijt} = y_{ijt} - T^{-1}\sum_{t=1}^{T} y_{ijt}$). Note that all time-invariant terms of equation (61) are swept out by the within-groups transformation, including the worker- and establishment-specific terms. Given the above assumptions, the within-groups estimator provides a consistent estimator for β_1 and γ_1.

Taking the first difference of equation (61) we get

$$\Delta y_{ijt} = \Delta x_{1it}\beta_1 + \Delta z_{1jt}\gamma_1 + \Delta\varepsilon_{ijt}. \tag{63}$$

Given the strict exogeneity assumption, the first-difference estimator is also consistent for the parameters associated with the time-variant variables in the model. We now present the estimates obtained from these two methods by sex and occupational group.

Table 10 shows the estimates of the coefficient associated with the establishment female proportion variable for both the within-groups and the first-difference methods. It also reports estimated standard error of the coefficient of interest and the P-value of the F-test for the significance of all parameters included in the regressions. The results show that the effect of working in predominantly female plants is negative and statistically significant (at least at the 10% level) for the all-female sample, and for females in blue-collar and clerical occupations, but it is statistically nil for females in the other two occupational groups. None of the results for males is statistically different from zero. We may conclude from these results that the effect of interest seems to be negative on female wages, but not (statistically) different from zero on male wages.

8.1.2 Multilevel-Mixed Models

Since we have a panel of workers that are employed in establishment units, we can view our data as structured in a hierarchical, multilevel fashion. More specifically, the data can be seen as having a three-level structure consisting of time periods (Level 1) nested within workers (Level 2) which are nested within establishments (Level-3). Typically, in multilevel modelling some parameters are treated as fixed, whereas others are assumed to be random.[53] In addition, multilevel models are specified through conditional relationships, that is, the relationships at one particular level are conditional on (generally unobserved) random coefficients of the higher levels in the model.[54]

[53] That is why these models are referred to as multilevel-mixed models.

[54] Widely cited references in multilevel modelling are Bryk and Raudenbush (1992) and Goldenstein (2002). A basic introduction can be found in Frees (2004).

Table 10: Within-Groups and First-Difference Estimates for the Proportion Female Coefficient by Sex and Occupational Group: Non-Mover Workers

	Within-Groups				First-Difference			
	Coeff.	Std-error	F-test	Observ.	Coeff.	Std-error	F-test	Observ.
Occupation/Sex	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Overall Sample								
1.1 - Females	-0.0526**	0.0268	0.0000	308743	-0.0504*	0.0264	0.0000	184549
1.2 - Males	0.0109	0.0352	0.0000	487861	0.0172	0.0359	0.0000	294384
2. Blue-Collar								
2.1 - Females	-0.0517*	0.0305	0.0000	173321	-0.0563*	0.0319	0.0000	103056
2.2 - Males	0.0498	0.0442	0.0000	331895	0.0578	0.0456	0.0000	199570
3. Clerical								
3.1 - Females	-0.0772*	0.0410	0.0033	87334	-0.0599	0.0406	0.0016	52450
3.2 - Males	-0.0507	0.0599	0.0059	62736	-0.0110	0.0566	0.0002	37898
4. Professional								
4.1 - Females	-0.0847	0.1421	0.3347	29495	-0.1609	0.1294	0.4702	17924
4.2 - Males	-0.0387	0.0917	0.2775	54058	-0.1244	0.0911	0.0904	33292
5. Managerial								
5.1 - Females	0.0300	0.1121	0.0004	18593	0.0828	0.1256	0.0002	11119
5.2 - Males	-0.0823	0.0787	0.0000	39172	-0.0768	0.0759	0.0000	23624

Notes:
1. The dependent variable is the log of the real hourly wage.
2. Significance levels::10% **:5% ***:1%.*
3. P-values reported for F-test in columns (3) and (7).
4. The within group regressions also include as regressors a quadratic in experience, establishment size, tenure, and year dummies. The first difference regressions also include a quadratic in experience and establishment size.

To make things more concrete, let the level-1 model equation be described by

$$y_{i,j,t} = \beta_{0ij} + \beta_{1ij}x_{i,j,t} + \gamma_{0j} + \gamma_{1j}z_{j,t} + \gamma_{2j}pfem_{j,t} + \epsilon_{i,j,t}, \tag{64}$$

where $x_{i,j,t}$ and $z_{j,t}$ are vectors that contain both time-invariant and time-variant observable variables at time t for worker i and establishment j, $pfem_{j,t}$ represents the female proportion at establishment j at time t, and $\epsilon_{i,j,t}$ is a disturbance term assumed to be normally distributed with mean zero and variance σ^2. The vector of parameters β_{0ij} and γ_{0j} are random intercepts, while β_{1ij}, γ_{1j}, and γ_{2j} are random slopes.

We specify the level-2 (workers) model as follows

$$\begin{aligned} \beta_{0ij} &= \beta_0 + u_{0ij} \\ \beta_{1ij} &= \beta_1, \end{aligned} \tag{65}$$

where β_0 and β_1 are fixed parameters, and u_{0ij} is a random variable that is allowed to vary across workers and establishments, and whose mean and variance are respectively zero and τ_0.

As for the level-3 (establishments) model, we specify it in two distinct ways. In the first we only allow γ_{0j} to be a random quantity, whereas in the second both γ_{0j} and γ_{2j}

are taken to be random. More specifically, the first level-3 specification is given by

$$\begin{aligned} \gamma_{0j} &= v_{0j} \\ \gamma_{1j} &= \gamma_1 \\ \gamma_{2j} &= \gamma_2, \end{aligned} \tag{66}$$

where γ_1 and γ_2 are fixed parameters, and v_{0j} is a mean-zero random variable with variance τ_1. The second specification is given by

$$\begin{aligned} \gamma_{0j} &= v_{0j}^* \\ \gamma_{1j} &= \gamma_1^* \\ \gamma_{2j} &= \gamma_2^* + v_{2j}, \end{aligned} \tag{67}$$

where γ_1^* and γ_2^* are fixed parameters, and v_{0j}^* and v_{2j} are mean-zero random variables with variances τ_1^* and τ_2, and covariance τ_{12}. Note that in the second specification the random coefficient associated with proportion of females (γ_{2j}) is allowed to vary across establishments.

Combining equations (64), (65), and (66) (or (67)) we obtain the combined model

$$y_{i,j,t} = \beta_0 + \beta_1 x_{i,j,t} + \gamma_1 z_{j,t} + \gamma_2 pfem_{j,t} + u_{0ij} + v_{0j} + \epsilon_{i,j,t} \tag{68}$$

or

$$y_{i,j,t} = \beta_0^* + \beta_1^* x_{i,j,t} + \gamma_1^* z_{j,t} + (\gamma_2^* + v_{2j}) pfem_{j,t} + u_{0ij}^* + v_{0j}^* + \epsilon_{i,j,t}^*, \tag{69}$$

where equation (68) uses the first specification of the establishment level equation, and equation (69) the second one. We use the asterisk notation to denote that the terms in equation (69) are not the same as in equation (68). We are interested in estimating the fixed parameters of the above equations (i.e. β_0, β_1, γ_1, and γ_2, or their asterisk counterparts), as well as the variance and covariance parameters associated with the random terms of those equations (i.e. σ^2, τ_0, τ_1, τ_2, and τ_{12}, or their asterisk versions).

Less general than the dynamic model framework, the multilevel-mixed model assumes that the unobserved terms (e.g. u_{0ij}^*, v_{0j}^*, v_{2j}, and $\epsilon_{i,j,t}^*$) are independent of the observed covariates. It is also assumed that there is no correlation between the random terms across the different levels.[55] In addition, it is assumed that they follow a multivariate normal distribution. Estimation is implemented via Concentrated Maximum Likelihood, in which the fixed coefficients are estimated through least squares and the parameters associated with the variances and covariances of the random terms are estimated by maximising a likelihood function in which the fixed coefficients estimated by least squares are substituted in the likelihood function. For all multilevel-based specifications we report the P-value of the likelihood ratio test where the unrestricted model is compared to the null, restricted model that imposes that the variances and covariance of the random terms are zero.[56]

Table 11 shows multilevel-mixed model results by sex. Columns (1) and (3) report the results based on equation (68), while columns (2) and (4) on equation (69).

The effect of proportion female on women's wages are estimated to be negative and statistically significant for both multilevel specifications, with the difference between these

[55]Note, however, that the random terms at the same level may be correlated. In the results, we report the estimates of the correlation between the random term associated with $pfem_{j,t}$ (v_{2j}) and the random intercept at the establishment level (v_{0j}^*).

[56]A Wald-type test might be not warranted for testing whether the variances are different from zero in this context, since it would be violating one of the underlying assumptions of maximum likelihood estimation, namely that the (true) parameters do not lie on the boundary of the parameter space.

Table 11: Multilevel Model Estimates by Sex: Non-Mover Workers

Covariates	Females: Random Intercepts (1)	Females: Random Intercepts and Slope (2)	Males: Random Intercepts (3)	Males: Random Intercepts and Slope (4)
Proportion female	-0.2674***	-0.2788***	-0.3188***	-0.2976***
	(0.0064)	(0.0067)	(0.0064)	(0.0075)
Experience	0.0105***	0.0108***	0.0261***	0.0267***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Experience square	-0.0001***	-0.0001***	-0.0003***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.0040***	0.0041***	0.0037***	0.0036***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Schooling	0.0960***	0.0958***	0.1005***	0.1002***
	(0.0007)	(0.0007)	(0.0006)	(0.0006)
Trade	-0.1313***	-0.1279***	-0.2873***	-0.2971***
	(0.0060)	(0.0061)	(0.0050)	(0.0050)
Services	0.0156**	0.0200***	-0.0744***	-0.0805***
	(0.0053)	(0.0054)	(0.0044)	(0.0044)
Clerical	0.1880***	0.1895***	0.0877***	0.0695***
	(0.0044)	(0.0044)	(0.0046)	(0.0047)
Professionals	0.8016***	0.8073***	0.5915***	0.5696***
	(0.0070)	(0.0070)	(0.0055)	(0.0056)
Managers	0.6170***	0.6163***	0.6354***	0.6298***
	(0.0074)	(0.0074)	(0.0057)	(0.0058)
Establishment size (1/10)	-0.0001***	-0.0001***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intercept	-0.1544***	-0.1523***	-0.0324**	-0.0309**
	(0.0131)	(0.0132)	(0.0109)	(0.0110)
Variance/Covariance Estimates				
σ^2	0.1390	0.1367	0.1568	0.1502
τ_0	0.1365	0.1454	0.1598	0.1435
τ_1	0.1355	0.2636	0.1606	0.1767
τ_2		0.3432		1.4104
τ_{12}		-0.7687		-0.4523
Log likelihood	-242520.2	-242181.8	-414813.1	-415750.7
Null model LR test [P-value]	0.0000	0.0000	0.0000	0.0000
Number of observations	308743	308743	487861	487861

Notes:
1. The dependent variable is the log of the real hourly wage. In the random intercepts specification only the level-2 (workers) and the level-3 (establishments) intercepts are random, while in the random intercepts and slope specification the proportion female slope is also random.
2. Standard errors in parentheses.
3. Significance levels:*:10% **:5% ***:1%.
4. All specifications include year dummies.

estimates being quite small. Compared to the null model, where the variance and covariance parameters associated with the random intercepts and slope are set to zero, the likelihood ratio test indicates that we cannot reject the hypothesis that these random terms belong to the model. Note that the estimate for the variance of the random slope associated with establishment female proportion (τ_2) suggests that the effect of gender segregation on female wages is heterogeneous across establishments. It is also interesting to note that the correlation between the establishment-level random intercept and the proportion-female random slope (τ_{12}) is negative, indicating that employers with higher managerial capacity and/or stronger discriminatory tastes against females tend to display a more negative relationship between female wages and gender segregation. The results for the other covariates have the expected sign, and are qualitatively similar to the dynamic model results

presented above.

As for males, the multilevel results also show that the relationship between establishment sex segregation and male wages is negative and statistically significant. As in the case of females, the null-model likelihood ratio test suggests that the model contains random coefficients. Also, the variance estimate for the proportion-female random slope (τ_2) indicates that there is heterogeneity across establishments in terms of the effect of gender segregation on male wages. The negative correlation between the establishment-level random intercept and the proportion-female random slope (τ_{12}) indicates that the relationship between sex segregation and male wages is more negative for more efficient/discriminatory employers. The results for the other covariates display the expected sign, and are similar to the dynamic model results.

Table 12 displays the estimates of the two multilevel specifications for females for each of the four occupational groups we have been working with. All estimates of the proportion female coefficient are negative and statistically significant at the 1% level. The null-model tests indicate that there is heterogeneity of intercepts and slopes for all occupational groups. The correlations between the establishment-level random intercept and the proportion-female random slope is negative for all occupational groups.

Table 13 displays multilevel results for males by occupational group. The estimates of the proportion female coefficient are negative for the blue-collar and the managerial occupational groups but not statistically different from zero for the clerical and professional groups. Again, the null-model tests indicate that there is heterogeneity of intercepts and slopes for all occupational groups. The correlations between the establishment-level random intercept and the proportion-female random slope is also negative for all occupational groups.

In sum, we may conclude from the multilevel results that the effect of establishment sex segregation on the wages of males and females is negative. These results also suggest that this effect is heterogeneous across establishments, and more negative for establishments with higher unobserved productivity and/or discriminatory tastes against female workers.

Table 12: Multilevel Model Estimates by Occupational Group for Females: Non-Mover Workers

	Blue-Collar		Clerical		Professional		Managerial	
Covariates	Random Intercepts (1)	Random Intercepts and Slope (2)	Random Intercepts (3)	Random Intercepts and Slope (4)	Random Intercepts (5)	Random Intercepts and Slope (6)	Random Intercepts (7)	Random Intercepts and Slope (8)
Proportion female	-0.1936***	-0.1902***	-0.2613***	-0.2756***	-0.3244***	-0.3424***	-0.3095***	-0.3614***
	(0.0108)	(0.0129)	(0.0151)	(0.0164)	(0.0396)	(0.0655)	(0.0349)	(0.0434)
Experience	0.0012	0.0015*	0.0172***	0.0173***	0.0078**	0.0089***	0.0234***	0.0243***
	(0.0007)	(0.0007)	(0.0013)	(0.0013)	(0.0024)	(0.0024)	(0.0034)	(0.0035)
Experience square	-0.0000	-0.0000	-0.0003***	-0.0003***	-0.0000	-0.0000	-0.0003***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Tenure	0.0022***	0.0021***	0.0027***	0.0027***	0.0016***	0.0015***	0.0021***	0.0020***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Schooling	0.0365***	0.0359***	0.0623***	0.0623***	0.0859***	0.0833***	0.0981***	0.0963***
	(0.0007)	(0.0007)	(0.0012)	(0.0012)	(0.0023)	(0.0024)	(0.0030)	(0.0031)
Trade	-0.0106	-0.0014	-0.1241***	-0.1211***	-0.0627	-0.1249	-0.1061**	-0.0889*
	(0.0107)	(0.0108)	(0.0181)	(0.0186)	(0.0633)	(0.0752)	(0.0381)	(0.0405)
Services	-0.1120***	-0.1056***	0.0642***	0.0731***	-0.0856	-0.1239	0.2398***	0.2661***
	(0.0107)	(0.0108)	(0.0177)	(0.0181)	(0.0572)	(0.0690)	(0.0380)	(0.0403)
Establishment size (1/10)	-0.0001**	-0.0001	0.0001	0.0001	0.0003	0.0002	0.0004	0.0004
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Intercept	0.4226***	0.4128***	0.1633***	0.1681***	0.7344***	0.8585***	0.1546*	0.1842**
	(0.0166)	(0.0176)	(0.0263)	(0.0269)	(0.0688)	(0.0840)	(0.0656)	(0.0692)
Variance/Covariance Estimates								
σ^2	0.1396	0.1360	0.1361	0.1331	0.1350	0.1110	0.1603	0.1419
τ_0	0.0647	0.0653	0.0998	0.1006	0.1520	0.1570	0.1486	0.1524
τ_1	0.1107	0.4055	0.1968	0.3196	0.3569	2.5124	0.3730	1.1436
τ_2		0.5849		0.3591		5.3726		1.9473
τ_{12}		-0.8958		-0.6549		-0.9363		-0.8458
Log likelihood	-109984.1	-109425.6	-61862.6	-61741.6	-22056.7	-21109.2	-16345.5	-16130.8
Null model LR test [P-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of observations	173321	173321	87334	87334	29495	29495	18593	18593

Notes:
1. The dependent variable is the log of the real hourly wage. In the random intercepts specification only the level-2 (workers) and the level-3 (establishments) intercepts are random, while in the random intercepts and slope specification the proportion female slope is also random.
2. Standard errors in parentheses.
3. Significance levels:*:10% **:5% ***:1%.
4. All specifications include year dummies.

Table 13: Multilevel Model Estimates by Occupational Group for Males: Non-Mover Workers

Covariates	Blue-Collar		Clerical		Professional		Managerial	
	Random Intercepts (1)	Random Intercepts and Slope (2)	Random Intercepts (3)	Random Intercepts and Slope (4)	Random Intercepts (5)	Random Intercepts and Slope (6)	Random Intercepts (7)	Random Intercepts and Slope (8)
Proportion female	-0.5288***	-0.5282***	0.0171	0.0230	-0.0238	0.0147	-0.1071***	-0.1050***
	(0.0068)	(0.0068)	(0.0236)	(0.0276)	(0.0378)	(0.0679)	(0.0369)	(0.0439)
Experience	0.0199***	0.0199***	0.0238***	0.0239***	0.0315***	0.0324***	0.0445***	0.0448***
	(0.0007)	(0.0007)	(0.0015)	(0.0015)	(0.0017)	(0.0017)	(0.0026)	(0.0026)
Experience square	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0004***	-0.0004***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.0038***	0.0038***	0.0024***	0.0024***	0.0014***	0.0013***	0.0012***	0.0012***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Schooling	0.0634***	0.0634***	0.0659***	0.0657***	0.1060***	0.1051***	0.1209***	0.1213***
	(0.0006)	(0.0006)	(0.0013)	(0.0013)	(0.0015)	(0.0015)	(0.0021)	(0.0021)
Trade	-0.2081***	-0.2070***	-0.1858***	-0.1874***	-0.3761***	-0.3622***	-0.2813***	-0.2971***
	(0.0051)	(0.0051)	(0.0258)	(0.0262)	(0.0521)	(0.0623)	(0.0352)	(0.0361)
Services	-0.1156***	-0.1168***	0.0241	0.0326	-0.2479***	-0.2276***	-0.0084	-0.0098
	(0.0045)	(0.0045)	(0.0251)	(0.0255)	(0.0463)	(0.0559)	(0.0352)	(0.0363)
Establishment size (1/10)	0.0005***	0.0004***	0.0003***	0.0002***	0.0009***	0.0005***	0.0009***	0.0008***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Intercept	0.3598***	0.3610***	0.0796*	0.0823*	0.2350***	0.2336***	-0.0609	-0.0507
	(0.0124)	(0.0124)	(0.0323)	(0.0328)	(0.0506)	(0.0613)	(0.0515)	(0.0526)
Variance/Covariance Estimates								
σ^2	0.1618	0.1617	0.1373	0.1328	0.1092	0.0978	0.2149	0.2052
τ_0	0.1113	0.0669	0.1137	0.1154	0.1476	0.1504	0.2196	0.2220
τ_1	0.1123	0.1625	0.2735	0.3131	0.4405	1.0027	0.4711	0.6156
τ_2		0.0011		0.8894		6.4232		2.1149
τ_{12}		-0.9986		-0.4625		-0.8216		-0.5585
Log likelihood	-266945.4	-266936.1	-45566.0	-45388.0	-35021.3	-34359.9	-38947.3	-38843.4
Null model LR test [P-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of observations	331895	331895	62736	62736	54058	54058	39172	39172

Notes:
1. The dependent variable is the log of the real hourly wage. In the random intercepts specification only the level-2 (workers) and the level-3 (establishments) intercepts are random, while in the random intercepts and slope specification the proportion female slope is also random.
2. Standard errors in parentheses.
3. Significance levels:*:10% **:5% ***:1%.
4. All specifications include year dummies.

8.2 All Workers Results

We end up our robustness checks by considering the complete sample of workers, that is, the data set that includes both non-mover workers and workers that change employers over time. Firstly, we present results for this complete data set using a similar multilevel framework as above. Secondly, we report within-groups and first-difference results that are obtained from a different specification of the unobserved specific terms in the wage equation.

8.2.1 Multilevel-Mixed Models

Since the multilevel model does not make use of the first-difference (or the within-groups) transformation, it becomes possible to use it on the complete data set. In other words, because the multilevel model is estimated without the removal of unmeasured specific terms from the estimating equation, it does not suffer from the problem of sweeping out the establishment-specific term when workers move across establishments over time. Thus, the multilevel model can be estimated using the complete data set. The specification of the model as well as the estimation procedure are the same as in the previous section.

Table 14 presents the multilevel model results for the complete data set by sex. The format of this Table is the same as that of Table 11.

The main point to notice is that the multilevel results based on the all-workers data set are qualitatively similar to the corresponding ones obtained when only non-mover workers were used for estimation (see Table 11). Indeed, the estimate of the proportion female coefficient is negative and statistically significant for males and females, with its magnitude being similar across the two data sets. This similarity of results gives us some indication that there was no particular bias because we were working with a sample of non-mover workers. As before, the null-model likelihood ratio tests indicates that there is heterogeneity in the random intercepts and the proportion-female random slope. The correlations between the establishment-level random intercept and the proportion-female random slope were also negative.

Tables 15 and 16 present the results by occupational group for females and males respectively. Each of these Tables displays similar results (in sign, statistical significance, and magnitude) as compared to the corresponding estimates based on the non-movers data set. Again, we capture the presence of heterogeneity in intercepts and slopes, and the correlation between the establishment-level random intercept and the proportion female random slope is negative throughout.

Table 14: Multilevel Model Estimates by Sex: All Workers

Covariates	Females: Random Intercepts (1)	Females: Random Intercepts and Slope (2)	Males: Random Intercepts (3)	Males: Random Intercepts and Slope (4)
Proportion female	-0.2364***	-0.2616***	-0.2868***	-0.2838***
	(0.0065)	(0.0069)	(0.0065)	(0.0075)
Experience	0.0122***	0.0126***	0.0256***	0.0262***
	(0.0008)	(0.0008)	(0.0007)	(0.0007)
Experience square	-0.0001***	-0.0001***	-0.0003***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.0039***	0.0039***	0.0038***	0.0037***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Schooling	0.0925***	0.0917***	0.0947***	0.0953***
	(0.0007)	(0.0007)	(0.0006)	(0.0006)
Trade	-0.1258***	-0.1196***	-0.2672***	-0.2716***
	(0.0061)	(0.0061)	(0.0052)	(0.0053)
Services	0.0064	0.0121*	-0.0960***	-0.1026***
	(0.0054)	(0.0054)	(0.0045)	(0.0046)
Clerical	0.2122***	0.2141***	0.1355***	0.1258***
	(0.0045)	(0.0045)	(0.0050)	(0.0052)
Professionals	0.8699***	0.8780***	0.6721***	0.6566***
	(0.0072)	(0.0073)	(0.0059)	(0.0061)
Managers	0.6889***	0.6840***	0.7144***	0.7094***
	(0.0079)	(0.0079)	(0.0061)	(0.0063)
Establishment size (1/10)	-0.0000***	-0.0001***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intercept	-0.1949***	-0.1804***	-0.0374***	-0.0419***
	(0.0135)	(0.0136)	(0.0113)	(0.0117)
Variance/Covariance Estimates				
σ^2	0.1423	0.1380	0.1606	0.1513
τ_0	0.0886	0.0941	0.0980	0.1377
τ_1	0.2582	0.6032	0.3315	0.3323
τ_2		0.7564		1.6416
τ_{12}		-0.8171		-0.4406
Log likelihood	-293761.8	-292415.3	-509583.8	-512140.2
Null model LR test [P-value]	0.0000	0.0000	0.0000	0.0000
Number of observations	341586	341586	544051	544051

Notes:
1. The dependent variable is the log of the real hourly wage. In the random intercepts specification only the level-2 (workers) and the level-3 (establishments) intercepts are random, while in the random intercepts and slope specification the proportion female slope is also random.
2. Standard errors in parentheses.
3. Significance levels:*:10% **:5% ***:1%.
4. All specifications include year dummies.

Table 15: Multilevel Model Estimates by Occupational Group for Females: All Workers

Covariates	Blue-Collar		Clerical		Professional		Managerial	
	Random Intercepts	Random Intercepts and Slope	Random Intercepts	Random Intercepts and Slope	Random Intercepts	Random Intercepts and Slope	Random Intercepts	Random Intercepts and Slope
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Proportion female	-0.1847***	-0.1806***	-0.2656***	-0.2807***	-0.2970***	-0.3130***	-0.3035***	-0.3905***
	(0.0111)	(0.0132)	(0.0155)	(0.0170)	(0.0403)	(0.0639)	(0.0375)	(0.0483)
Experience	0.0027***	0.0028***	0.0176***	0.0176***	0.0099***	0.0106***	0.0275***	0.0283***
	(0.0007)	(0.0007)	(0.0014)	(0.0014)	(0.0026)	(0.0026)	(0.0037)	(0.0036)
Experience square	-0.0000*	-0.0000*	-0.0003***	-0.0003***	-0.0001	-0.0001	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Tenure	0.0023***	0.0023***	0.0027***	0.0027***	0.0015***	0.0015***	0.0019***	0.0017***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Schooling	0.0330***	0.0325***	0.0604***	0.0602***	0.0844***	0.0821***	0.1009***	0.0997***
	(0.0007)	(0.0007)	(0.0012)	(0.0013)	(0.0026)	(0.0026)	(0.0032)	(0.0032)
Trade	-0.0110	-0.0048	-0.1261***	-0.1233***	-0.1094	-0.1741*	-0.1462***	-0.1268**
	(0.0112)	(0.0112)	(0.0187)	(0.0192)	(0.0657)	(0.0774)	(0.0417)	(0.0437)
Services	-0.1182***	-0.1143***	0.0763***	0.0862***	-0.1242*	-0.1474*	0.2110***	0.2365***
	(0.0112)	(0.0112)	(0.0183)	(0.0188)	(0.0602)	(0.0718)	(0.0415)	(0.0434)
Establishment size (1/10)	-0.0001**	-0.0001	0.0001	0.0001	0.0002	0.0002	0.0004	0.0004
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Intercept	0.3952***	0.3879***	0.1602***	0.1659***	0.7857***	0.8973***	0.1493*	0.2000**
	(0.0171)	(0.0182)	(0.0277)	(0.0284)	(0.0732)	(0.0877)	(0.0706)	(0.0744)
Variance/Covariance Estimates								
σ^2	0.1480	0.1437	0.1420	0.1380	0.1419	0.1156	0.1647	0.1402
τ_0	0.0962	0.0967	0.1579	0.4302	0.2369	0.2485	0.1961	0.2025
τ_1	0.1400	0.5435	0.2248	0.2132	0.4039	2.6620	0.4958	1.6661
τ_2		0.7424		0.3643		5.4780		3.0504
τ_{12}		-0.9077		-0.7250		-0.9344		-0.8740
Log likelihood	-139549.5	-138743.6	-75329.7	-75180.9	-27097.4	-26169.5	-18232.4	-17899.0
Null model LR test [P-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of observations	195779	195779	94707	94707	31965	31965	19135	19135

Notes:
1. The dependent variable is the log of the real hourly wage. In the random intercepts specification only the level-2 (workers) and the level-3 (establishments) intercepts are random, while in the random intercepts and slope specification the proportion female slope is also random.
2. Standard errors in parentheses.
3. Significance levels:*:10% **:5% ***:1%.
4. All specifications include year dummies.

Table 16: Multilevel Model Estimates by Occupational Group for Males: All Workers

Covariates	Blue-Collar		Clerical		Professional		Managerial	
	Random Intercepts	Random Intercepts and Slope	Random Intercepts	Random Intercepts and Slope	Random Intercepts	Random Intercepts and Slope	Random Intercepts	Random Intercepts and Slope
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Proportion female	-0.4784***	-0.5100***	-0.0041	0.0090	0.0021	0.0886	-0.0563	-0.0538
	(0.0068)	(0.0080)	(0.0247)	(0.0295)	(0.0384)	(0.0696)	(0.0384)	(0.0468)
Experience	0.0215***	0.0221***	0.0229***	0.0231***	0.0308***	0.0321***	0.0440***	0.0446***
	(0.0008)	(0.0008)	(0.0016)	(0.0016)	(0.0020)	(0.0020)	(0.0029)	(0.0029)
Experience square	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0004***	-0.0004***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Tenure	0.0042***	0.0042***	0.0025***	0.0024***	0.0014***	0.0013***	0.0012***	0.0011***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Schooling	0.0607***	0.0622***	0.0632***	0.0629***	0.1068***	0.1050***	0.1205***	0.1200***
	(0.0006)	(0.0007)	(0.0015)	(0.0015)	(0.0018)	(0.0018)	(0.0023)	(0.0024)
Trade	-0.1881***	-0.1892***	-0.1978***	-0.1985***	-0.3603***	-0.3469***	-0.3073***	-0.3238***
	(0.0052)	(0.0054)	(0.0276)	(0.0273)	(0.0522)	(0.0623)	(0.0364)	(0.0380)
Services	-0.1280***	-0.1274***	0.0326	0.0385	-0.2278***	-0.2222***	-0.0114	-0.0151
	(0.0046)	(0.0048)	(0.0266)	(0.0265)	(0.0461)	(0.0556)	(0.0364)	(0.0381)
Establishment size (1/10)	0.0004***	0.0004***	0.0002*	0.0001*	0.0007***	0.0004**	0.0008***	0.0007**
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Intercept	0.2881***	0.2745***	0.1178***	0.1198***	0.2581***	0.2483***	-0.0191	-0.0034
	(0.0127)	(0.0133)	(0.0352)	(0.0350)	(0.0532)	(0.0627)	(0.0559)	(0.0575)
Variance/Covariance Estimates								
σ^2	0.1676	0.1554	0.1351	0.1297	0.1128	0.1008	0.2264	0.2118
τ_0	0.0657	0.1105	0.1815	0.1825	0.2928	0.2848	0.3642	0.3676
τ_1	0.2388	0.2408	0.3227	0.2954	0.4549	1.4755	0.4908	0.7274
τ_2		1.5323		1.2426		7.5226		2.8608
τ_{12}		-0.4804		-0.3596		-0.8027		-0.6128
Log likelihood	-338979.2	-342174.4	-51230.2	-50958.3	-44925.7	-44103.4	-44663.2	-44511.2
Null model LR test [P-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of observations	381139	381139	64427	64427	57547	57547	40938	40938

Notes:
1. The dependent variable is the log of the real hourly wage. In the random intercepts specification only the level-2 (workers) and the level-3 (establishments) intercepts are random, while in the random intercepts and slope specification the proportion female slope is also random.
2. Standard errors in parentheses.
3. Significance levels:*:10% **:5% ***:1%.
4. All specifications include year dummies.

8.2.2 Within-Groups and First-Difference

As a final robustness check, we employ the within-groups and first-difference methods on the all-workers data set. For that we re-specify equation (61) in the following manner

$$y_{ijt} = x_{1it}\beta_1 + x_{2i}\beta_2 + z_{1jt}\gamma_1 + z_{2j}\gamma_2 + \eta_{ij} + \varepsilon_{ijt}. \tag{70}$$

Note that instead of specifying separate fixed effects for workers and establishments (see equation (61)), we now assume a more general specification where we allow for one specific term that varies across each pair worker/establishment.[57] So, taking either a within-groups or a first-difference transformation of the data for each pair worker/establishment we can sweep out the term η_{ij} from equation (70).[58] Notice that this allows the use of the complete data set, since incorporating workers that change establishments over time does not preclude the removal of the worker/establishment specific term in the present setting. We maintain the assumptions that the covariates are strictly exogenous, and that the variance of the disturbance term, ε_{ijt}, may be clustered within establishment units.

In Table 17 we present the within-groups and first-difference estimates of the female proportion coefficient by sex and occupational group. Overall, the results are very similar to the ones corresponding to the non-movers sample (see Table 10). The estimates are negative and significant (at least at the 10% level) for the all-female group and for females in blue-collar and clerical occupations, and not statistically different from zero for males. Again, the similarity between the results from the non-mover sample and the complete sample indicates that the former sample does not seem to be a selective sample of the population of interest.

9 Discussion

9.1 Summary of Empirical Results

So far we have presented results from several different methods by sex and occupational group. As an attempt to summarise all these results, in Table 18 we averaged the estimates of the proportion female coefficient that were obtained across the different methods/specifications by sample group.[59] Panel A of the Table presents the averages for females and Panel B for males. All averages were computed from the estimates that were statistically significant at least at 10% level. The first two columns display the averages only for the coefficient estimates that were obtained from the non-movers data set, while the last two columns display the average estimates from both the non-movers and the all-workers data sets. Since the number of observations used to estimate the coefficient of interest varied across the different methods and sample groups, we present both unweighted (columns (1) and (3)) as well as weighted (columns (2) and (4)) averages of the

[57] This specification is more general in the sense that we do not impose separability of the unobserved specific terms as in equation (61). In other words, assuming that the model contains $(\theta_i^* + \phi_j^*)$ is just a special case of postulating that it contains η_{ij}.

[58] Let k index each pair worker/establishment. The within-groups transformation of equation (70) gives $\widetilde{y_{ijt}} = \widetilde{y_{kt}} = \widetilde{x_{kt}}\beta_1 + \widetilde{z_{jt}}\gamma_1 + \widetilde{\varepsilon_{kt}}$, where for instance $\widetilde{y_{kt}} = y_{kt} - T^{-1}\sum_{t=1}^{T} y_{kt}$. Note that $T^{-1}\sum_{t=1}^{T}\eta_{ij} = T^{-1}\sum_{t=1}^{T}\eta_k = \eta_k = \eta_{ij}$.

[59] Altogether there were seven distinct methods/specifications: 1) Difference-GMM, 2) One-Step-System-GMM, 3) Two-Step-System-GMM, 4) Within-Groups, 5) First-Differences, 6) Multilevel-Random-Intercepts, 7) Multilevel-Random-Intercepts-Slope. We classify the sample groups as follows: 1) All females, 2) Females in blue-collar occupations, 3) Females in clerical occupations, 4) Females in professional occupations, 5) Females in managerial occupations, and the same five groups for males.

Table 17: Within-Groups and First-Difference Estimates for the Proportion Female Coefficient by Sex and Occupational Group: All Workers

	Within-Groups				First-Difference			
	Coeff.	Std-error	F-test	Observ.	Coeff.	Std-error	F-test	Observ.
Occupation/Sex	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Overall Sample								
1.1 - Females	-0.0528*	0.0281	0.0000	341586	-0.0510*	0.0277	0.0000	178778
1.2 - Males	0.0159	0.0353	0.0000	544051	0.0194	0.0359	0.0000	287101
2. Blue-Collar								
2.1 - Females	-0.0517*	0.0313	0.0000	195779	-0.0596*	0.0324	0.0000	100694
2.2 - Males	0.0495	0.0438	0.0000	381139	0.0573	0.0453	0.0000	196144
3. Clerical								
3.1 - Females	-0.0754*	0.0438	0.0058	94707	-0.0576	0.0441	0.0016	50289
3.2 - Males	-0.0530	0.0622	0.0245	64427	-0.0088	0.0583	0.0005	35811
4. Professional								
4.1 - Females	-0.1039	0.1467	0.4888	31965	-0.1679	0.1343	0.3369	17442
4.2 - Males	-0.0360	0.0956	0.3322	57547	-0.1272	0.0954	0.1352	32564
5. Managerial								
5.1 - Females	0.0389	0.1203	0.0007	19135	0.0966	0.1360	0.0010	10353
5.2 - Males	-0.0404	0.0891	0.0000	40938	-0.0750	0.0804	0.0000	22582

Notes:
1. The dependent variable is the log of the real hourly wage.
2. Significance levels::10% **:5% ***:1%.*
3. P-values reported for F-test in columns (3) and (7).
4. The within group regressions also include as regressors a quadratic in experience, establishment size, tenure, and year dummies. The first difference regressions also include a quadratic in experience and establishment size.

estimates. The weights are the share of the number of observations for each pair of sample group and method/specification we have used. For each combination of data set and form of weighting, we present the average of the estimates, its standard error (rows below the averages), and the number of estimates that were used to compute the averages (rows below the standard errors).

A first point to notice from Table 18 is that all computed averages have a negative sign. This occurs irrespectively of the sample group, the data sets used, or the form of weighting. Secondly, although the number of coefficient estimates used to compute the averages is small, their standard errors are not large. Indeed, the upper bound of the 95% confidence interval (not shown) is negative for every single mean of the estimates.[60]

As we previously noted, the individual estimates obtained from the all-workers data set were not too much different from the corresponding ones from the non-movers sample. This is confirmed by the comparison between the computed averages in columns (1) and (3) or in columns (2) and (4). We may conclude therefore that there is no substantial selective bias in using information only for workers that remained at the same establishment over time. It should be also noticed that the unweighted and weighted averages are of similar magnitude.

[60]This could not be calculated for males in clerical occupations because there is just one statistically significant estimate for this group.

Table 18: Average of Estimates of the Establishment Female Proportion Coefficient

Group	Non-Movers		Non-Movers and All Workers	
	Unweighted (1)	Weighted (2)	Unweighted (3)	Weighted (4)
A - FEMALES				
A.1 - All	-0.1407	-0.1555	-0.1446	-0.1593
	(0.0428)	(0.0452)	(0.0324)	(0.0333)
	6	6	10	10
A.2 - Blue-Collar	-0.1547	-0.1523	-0.1405	-0.1410
	(0.0322)	(0.0316)	(0.0237)	(0.0229)
	6	6	10	10
A.3 - Clerical	-0.2177	-0.2206	-0.2142	-0.2149
	(0.0355)	(0.0373)	(0.0299)	(0.0311)
	6	6	9	9
A.4 - Professional	-0.3682	-0.3726	-0.3501	-0.3464
	(0.0403)	(0.0343)	(0.0302)	(0.0258)
	5	5	7	7
A.5 - Managerial	-0.3355	-0.3355	-0.3412	-0.3413
	(0.0259)	(0.0259)	(0.0209)	(0.0210)
	2	2	4	4
B - MALES				
B.1 - All	-0.2569	-0.2696	-0.2664	-0.2760
	(0.0301)	(0.0293)	(0.0200)	(0.0177)
	4	4	6	6
B.2 - Blue-Collar	-0.5116	-0.5158	-0.5058	-0.5068
	(0.0098)	(0.0095)	(0.0083)	(0.0087)
	4	4	6	6
B.3 - Clerical	-0.2555	-0.2555	-0.2555	-0.2555
	(.)	(.)	(.)	(.)
	1	1	1	1
B.4 - Professional	-0.2828	-0.2828	-0.2828	-0.2828
	(0.0661)	(0.0661)	(0.0661)	(0.0661)
	2	2	2	2
B.5 - Managerial	-0.1911	-0.1618	-0.1911	-0.1618
	(0.0408)	(0.0385)	(0.0408)	(0.0385)
	5	5	5	5

Notes:
1. Non-mover data set refers to the estimates that were obtained from data on workers that remained at the same establishment over time. All workers data set corresponds to the data that also includes those workers that changed establishments over time.
2. The weights used to obtain the weighted averages were the proportion of the number of observations that were used in the estimation of the coefficient across the different econometric methods/specifications employed. The sum of the weights is always one.
3. Standard errors in parentheses.
4. Numbers below standard errors refer to the number of estimates used to compute the averages.

In sum, the results summarized in Table 18 indicate that the effect of establishment female segregation on wages is negative for both gender groups. In the following section we compare these results with cross-section estimates obtained in the previous related literature and with our own estimates.

9.2 Comparison with Cross-Section Results

In section 2 we presented a survey of previous empirical research on the connection between establishment gender segregation and wages. Recalling that the results of those studies were based on cross-section data, for comparison purposes we try to reproduce their empirical framework here by running cross-section regressions that use the most common specifications that were used in those studies.[61] Apart from comparing our cross-section results with those of the related empirical literature, we also contrast our previous results with those obtained in this section.

We implement two distinct specifications. The first is OLS regression by sex, and the second is OLS regression with pooled (by sex) data, where we include an interaction term between a female dummy and the variable establishment female proportion. These two specifications are implemented on cross-section data and, for comparison with our previous results, on the data for all years together. The results are presented in Table 19, where columns (1) to (3) correspond to the cross-section results and the last three columns to the all-years results. Columns (1) and (4) show the regression results based on female data, columns (2) and (5) on male data, and columns (3) and (6) on pooled data. All our cross-section estimates refer to the first year of our data (i.e. 2000), but very similar results are obtained for each of the other two years.

As can be seen from Table 19, the estimated female proportion coefficient is negative and statistically significant at the 1% level for the two sex groups and across the two specifications we use. Overall, this confirms what has been found in the previous literature. What seems to be different however from previous research is the differential impact of establishment gender segregation on the wages of the two sex groups. Indeed, in contrast to what was established in the literature, our cross-section results indicate that the effect of working in largely female plants is stronger (i.e. more negative) on men's wages than on women's wages.

We now compare our OLS results with those that we have obtained in the previous sections. Looking at the female case first, if we take our computed averages across all models we have used before (see row (A.1) in Table 18), there is a substantial reduction in the effect of establishment gender segregation on female wages when we pass from the OLS (both cross-section and all-years) to the panel data results. Indeed, while the OLS estimates are around -0.30, the average for all statistically significant estimates is approximately -0.15. This is also confirmed for the comparison with the estimates from most single panel-data models. The only exception is the multilevel model estimates, for which the magnitude of the female proportion coefficient is only slightly less negative than the OLS ones.

As for the male results, the comparison also shows an important reduction in estimates. Indeed, if we take the average for the statistically significant panel-data estimates, -0.26, (see row (B.1) in Table 18), there is a substantial reduction as compared to OLS estimates, -0.40. All estimates from single panel-data models corroborate this assertion.

The above comparisons suggest that the estimation of the effect of establishment gender segregation on wages is affected by the inclusion of unobservable worker- and establishment-specific effects in the model. In other words, the establishment gender composition effect on wages reflects in part unmeasured worker-specific traits and unmeasured establishment-specific characteristics that are correlated both with wages and the establishment female composition. Hence, when the wage equation is estimated without the inclusion of unmea-

[61] It should be pointed out that since the previous studies use a variety of control variables, our results are not strictly comparable to theirs.

Table 19: OLS Estimates for Males and Females: Cross-Section and All Years

Covariates	Year 2000			All years		
	Females	Males	Pooled	Females	Males	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
Female proportion	-0.3020***	-0.3856***	-0.4248***	-0.3094***	-0.3719***	-0.4103***
	(0.0085)	(0.0084)	(0.0081)	(0.0050)	(0.0049)	(0.0047)
Establishment size (1/10)	-0.0000***	0.0002***	0.0001***	-0.0001***	0.0002***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience	0.0112***	0.0267***	0.0190***	0.0097***	0.0252***	0.0174***
	(0.0009)	(0.0008)	(0.0006)	(0.0005)	(0.0005)	(0.0004)
Experience square	-0.0001***	-0.0003***	-0.0002***	-0.0001***	-0.0003***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.0039***	0.0035***	0.0037***	0.0042***	0.0037***	0.0039***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Trade	-0.1406***	-0.2924***	-0.2328***	-0.1356***	-0.2924***	-0.2312***
	(0.0073)	(0.0059)	(0.0046)	(0.0042)	(0.0035)	(0.0027)
Services	0.0208**	-0.0472***	-0.0214***	0.0156***	-0.0718***	-0.0390***
	(0.0064)	(0.0051)	(0.0040)	(0.0038)	(0.0030)	(0.0024)
Clerical	0.1890***	0.0844***	0.1396***	0.1827***	0.0878***	0.1392***
	(0.0054)	(0.0054)	(0.0038)	(0.0031)	(0.0032)	(0.0022)
Professionals	0.7718***	0.5451***	0.6236***	0.7898***	0.5759***	0.6523***
	(0.0085)	(0.0064)	(0.0051)	(0.0049)	(0.0038)	(0.0030)
Managers	0.6329***	0.6600***	0.6529***	0.6067***	0.6294***	0.6231***
	(0.0090)	(0.0067)	(0.0053)	(0.0052)	(0.0040)	(0.0032)
Intercept	-0.1656***	-0.0578***	0.0257**	-0.1152***	-0.0013	0.0741***
	(0.0160)	(0.0128)	(0.0099)	(0.0096)	(0.0079)	(0.0061)
Female			-0.2842***			-0.2684***
			(0.0060)			(0.0035)
Female $\times$ Female Proportion			0.1350***			0.1158***
			(0.0118)			(0.0069)
R^2	0.5323	0.5244	0.5409	0.4988	0.4836	0.5022
Number of observations	92907	148701	241608	308743	487861	796604

Notes:
1. The dependent variable is the log of the real hourly wage.
2. Standard errors in parentheses.
3. Significance levels:*:10% **:5% ***:1%.
4. The all-years specifications include year dummies.

sured worker- and firm-specific effects (as in the cross-section/OLS models), the coefficient on establishment female proportion tends to be biased. Indeed, the fact that the longitudinal estimates are less negative than the cross-section ones indicate that this bias is negative, thus suggesting the existence of a negative correlation between the establishment female proportion variable and the unmeasured effects.[62] We conclude therefore that unmeasured worker- and establishment-specific effects do matter for the relationship between wages and establishment gender composition.

One possible explanation for the negative correlation between establishment female composition and the unobserved specific effects is that (observationally identical) men and women with lower unmeasured skills are more likely to be employed in predominantly female establishments. Alternatively, employers with higher (lower) unmeasured productivity and/or stronger (weaker) discriminatory tastes against females are more likely to hire relatively more males (females).

In terms of the predictions of the two models we developed above, the statistical discrimination model (see section 3.3) is compatible with negative gender composition effects on the wages of males and females. The monopsonistic model of employer discrimination

[62]Working with gender segregation at the occupational level Macpherson and Hirsch (1995) also finds that the longitudinal estimates of the gender composition effect on wages is less negative than the cross-section ones.

(see section 3.2) is more flexible in that it predicts various possible signs for the establishment gender composition effect on the wages of the two sex groups. In particular, there is a set of the model's parameter values within which the female composition effect is negative on both gender wages.[63]

9.3 The Effect on Gender Wage Gap

In this section we present the results of the widely used Oaxaca-Blinder decomposition of the gender wage gap.[64] As it is well known, this decomposition is a technique intended to measure how much of the gender wage gap is due to differences in coefficients obtained from two separately estimated wage regressions (one for each sex), and how much can be attributed to differences in (average) characteristics of the sexes. The first component is associated with differential "rewards" to each of the sexes's characteristics, and it is typically seen as the part of the wage gap that is unjustified or discriminatory. The second component corresponds to differences in "endowments" between the two groups, and it is usually considered the justified or non-discriminatory portion of the gender wage gap.[65] More generally, this decomposition is typically seen as a comparison between the wage structures of the two sexes in relation to the wage structure that would prevail in the absence of discrimination.

Expressed in a simple way, the decomposition starts with the following two regressions (omitting subscripts):

$$\begin{aligned} ln(w_m) &= X_m\beta_m + e_m && (71) \\ ln(w_f) &= X_f\beta_f + e_f, && (72) \end{aligned}$$

where m and f denote males and females respectively, X, which includes a constant term, is a vector of characteristics of workers and establishments, β is a conformable vector of parameters, and e is a disturbance term. Given the regression property that the residuals have zero mean, we can use equations (71) and (72) to obtain

$$\overline{ln(w_m)} - \overline{ln(w_f)} = \overline{X_m}b_m - \overline{X_f}b_f, \quad (73)$$

where the over-bar denotes averages and b_g, $g = m, f$, represent estimated coefficients. Adding and subtracting from equation (73) the term $\overline{X_f}b_m$ or the term $\overline{X_m}b_f$ produces two distinct decompositions of the overall differential in average wages:

$$\begin{aligned} \overline{ln(w_m)} - \overline{ln(w_f)} &= (b_m - b_f)\overline{X_f} + (\overline{X_m} - \overline{X_f})b_m && (74) \\ &= (b_m - b_f)\overline{X_m} + (\overline{X_m} - \overline{X_f})b_f. && (75) \end{aligned}$$

The first terms on the RHS of these two equations measure how much of the wage gap is due to differences in coefficients, where these differences are weighted by either $\overline{X_f}$ or $\overline{X_m}$. This is the part of the gap that is considered discriminatory. The second terms on the RHS capture how much of the gap is attributable to differences in the mean of the variables included in the male and female regressions. For these terms, the weights are given by the coefficients from either the male regression (b_m) or the female one (b_f). This is the

[63] This corresponds to case C in Table 2.

[64] Oaxaca (1973) and Blinder (1973).

[65] In fact, differences in endowments between the two gender groups may be a consequence of past or present discrimination against women. For instance, if women perceive that they are discriminated against by employers, they may have less incentives to acquire human capital, so part of the gender differences in human capital can be considered discriminatory.

part of the gap that is referred to as the non-discriminatory part. We term equation (74) the male-based decomposition, for it is the vector b_m that is used as the counterfactual structure of no-discrimination. Equation (75) is termed the female-based decomposition.

Clearly, equations (74) and (75) do not necessarily entail the same results. This is a common problem with index numbers. One possible solution to that is to define the vector of coefficients $b = Wb_m + (I - W)b_f$, where W is a matrix of weights and I the identity matrix. If we now add and subtract the terms $\overline{X_m}b$ and $\overline{X_f}b$ from equation (73) we obtain after some rearrangements

$$\overline{ln(w_m)} - \overline{ln(w_f)} = (\overline{X_m}(I-W) + \overline{X_f}W)(b_m - b_f) + (Wb_m + (I-W)b_f)(\overline{X_m} - \overline{X_f}). \quad (76)$$

This is a more flexible equation in the sense that it allows the analyst to choose how much weight he/she wants to give to each of the two gender wage structures. We present results for three different choices of W: (i) $W = I$, which reduces to the male-based decomposition of equation (74), (ii) $W = 0$, which gives the female-based decomposition of equation (75), and (iii) $W = 0.5I$, which produces an average that lies half-way between the two previous cases.

Another possible solution has been proposed by Neumark (1988) and Oaxaca and Ransom (1988), who suggest that the coefficients from a pooled (by sex) wage regression can be used as the non-discriminatory wage structure for decomposing the wage gap

$$\overline{ln(w_m)} - \overline{ln(w_f)} = \overline{X_m}(b_m - b^*) + \overline{X_f}(b_f - b^*) + (\overline{X_m} - \overline{X_f})b^*, \quad (77)$$

where b^* is the estimated vector of coefficients from the pooled regression. The summation of the first two terms on the RHS represent the differences in coefficients, and the last term captures the differences in characteristics.

Our main goal with this decomposition analysis is to find out how much of the gender wage gap in Brazil can be attributed to gender segregation across establishments. Therefore, we focus our attention on the contributions of the two components of the proportion female variable to the overall gap. We have chosen to use our most general econometric model to implement these decompositions. More specifically, we use the estimates from the one-step system GMM model of Table 5. It should be pointed out however that somewhat different decomposition results would emerge if we used the estimated coefficients from the other models/specifications we have previously employed.

Table 20 presents the results of the four decompositions we have implemented: columns (A) and (B) contain respectively the male-based and the female-based decompositions results, column (C) the average-based results, and column (D) the pooled-based ones. Row (1) displays the mean log wage gap between males and females. Panel A presents the contributions of the two components of the decompositions (i.e. characteristics and coefficients) when all characteristics are considered (rows (2) and (3)), while panel B displays the contributions of these two components only for the proportion female variable (rows (4) and (5)). The percent contribution of each component to overall gap is presented in rows (2.a) and (3.a) of panel A. Panel B contains the percent contribution of each component of the proportion female variable to overall gap (rows (4.a) and (5.a)) as well as their percent contribution to their respective overall components (rows (4.b) and (5.b)).

Looking first at the decomposition results presented in panel A, we see that the first three forms of decomposition give similar results in terms of the contributions of the two components of the decomposition. Indeed, these three decompositions reveal that the differences in attributes contribute to 46% of the gender wage gap, with the differences

Table 20: Oaxaca-Blinder Log Wage Decompositions

	Male-Based (A)	Female-Based (B)	Average-Based (C)	Pooled-Based (D)
(1) - Wage Gap	0.3571	0.3571	0.3571	0.3571
A - ALL CHARACTERISTICS				
(2) - Different Characteristics	0.1702	0.1578	0.1640	0.2416
(2.a) - Percent (2)/(1)	47.7	44.2	45.9	67.7
(3) - Different Coefficients	0.1869	0.1993	0.1931	0.1155
(3.a) - Percent (3)/(1)	52.3	55.8	54.1	32.3
B - PROPORTION FEMALE				
(4) - Different Characteristics	0.0657	0.0296	0.0477	0.0787
(4.a) - Percent (4)/(1)	18.4	8.3	13.3	22.0
(4.b) - Percent (4)/(2)	38.6	18.8	29.1	32.6
(5) - Different Coefficients	-0.0622	-0.0262	-0.0442	-0.0752
(5.a) - Percent (5)/(1)	-17.4	-7.3	-12.4	-21.1
(5.b) - Percent (5)/(3)	-33.3	-13.1	-22.9	-65.1

Notes: (Fe)Male-based uses estimated coefficients from the (fe)male regression as the reference non-discriminatory situation. Average-based weights the estimated coefficients from each regression by a value of 0.5 to give the reference comparison. Pooled-based uses the estimated coefficients from a pooled regression as the reference non-discriminatory situation. Wage gap refers to the mean log wage gap between males and females.

in coefficients absorbing the other 54%. In contrast, the pooled-based decomposition reveals that former component dominates the latter, a finding that is more in line with the international literature.[66]

The results presented in panel B show that the contribution of the difference in the proportion female coefficients is negative (row (5)), whereas the contribution of the difference in the mean proportion female is positive (row (4)). This implies that the former component reduces the wage gap, while the latter increases it.[67] It is interesting to note that the contribution of the difference in mean proportion female is relatively high, representing from 8% to 22% of the overall wage gap (row (4.a)), and from 19% to 39% of the contribution of all characteristics to this gap (row (4.b)).[68] As a result, changes in the degree of establishment female segregation could have important impacts in reducing the gender wage gap. In the next section we present a crude attempt to measure these impacts.

[66] See e.g. Neumark (1988), Oaxaca and Ransom (1988), and Reilly and Wirjanto (1999a).

[67] Notice that these two effects tend cancel each other out, meaning that the overall contribution of the proportion female variable is almost negligible to gender wage gap. Though not shown, using the pooled-based decomposition the most important contributions are: experience (99%), experience square (-34%), and schooling (25%).

[68] Using the pooled-based decomposition, the difference in mean proportion female between the sexes is the single most important contribution among all differences in mean characteristics both to the overall wage gap and to the contribution of all characteristics.

9.4 Policy Considerations

There are many different policies that have been proposed to reduce the gender wage differential. We may roughly divide them in two groups.[69] The first focuses on "prices" in the sense that it aims to equalise the wages of men and women that are in similar occupations within the same establishment. This is the goal of comparable worth and equal pay provisions.[70] The second type of policies focuses on "quantities" in the sense that it tries to provide equal employment opportunities to females across different establishments. Examples of such policies are employment equity programmes and affirmative action initiatives. While this second type of policies intends to reduce establishment gender segregation, the first type does not.

In theory, both types of policies are capable of reducing the gender wage gap. Despite that, we focus our attention here on the impacts of the second type of policies. More specifically, we follow the methodology proposed by Reilly and Wirjanto (1999a) so as to assess the impact of an hypothetical employment equity programme on the gender wage gap. The idea is to fix the establishment female proportion at some pre-specified levels and then compute the magnitude of the change in the gender wage gap that would be generated when all establishments are constrained to obey such policy targets. In doing so it is assumed that the policy maker can only change "quantities" (i.e. the female composition of establishments), but not "prices" (i.e. the coefficients associated with the female composition).

In order to compute the impacts of this hypothetical programme we use the Oaxaca-Blinder decomposition framework presented in the previous section. Specifically, we initially write

$$\overline{ln(w_m)} - \overline{ln(w_f)} = \overline{p_m} b_{m,pfem} - \overline{p_f} b_{f,pfem} + (\overline{X_m^*} b_m^* - \overline{X_f^*} b_f^*), \tag{78}$$

where $\overline{p_m}$ is the mean proportion of females for the male group, $\overline{p_f}$ is the mean proportion of females for the female group, $b_{g,pfem}$, $g = m, f$, are the estimated coefficient associated with the proportion female variable in the male and female regressions, and $\overline{X_g^*} b_g^*$, $g = m, f$, represent the product of all other mean characteristics and their corresponding coefficients from those regressions, including the intercept.

Suppose the policy constrains establishments to have a fixed proportion of females, which we denote by $\overline{p_p}$, so that the net-wage that the average male and the average female would receive under this policy would be respectively

$$\overline{ln(w_m)}^p = \overline{p_p} b_{m,pfem} + \overline{X_m^*} b_m^* \tag{79}$$

$$\overline{ln(w_f)}^p = \overline{p_p} b_{f,pfem} + \overline{X_f^*} b_f^*. \tag{80}$$

Adding and subtracting equations (79) and (80) from equation (78) we get after some rearrangements that

$$\overline{ln(w_m)} - \overline{ln(w_f)} = (\overline{p_m} - \overline{p_p}) b_{m,pfem} + (\overline{p_p} - \overline{p_f}) b_{f,pfem} + (b_{m,pfem} - b_{f,pfem}) \overline{p_p} + \Delta, \tag{81}$$

where $\Delta = (\overline{X_m^*} b_m^* - \overline{X_f^*} b_f^*)$. Equation (81) can be used to analyse the impact of fixing the female proportion across establishments on the gender wage gap. The first (second)

[69] We are only considering those policies that attack the problem directly at the establishment (or firm) level. There are other policies that are not strictly based at the establishment level such as educational and training initiatives.

[70] For instance, if there are two occupations of similar worth at an establishment, with one being typically held by women and the other by men (e.g. secretaries and truck drivers), the comparable worth policy states that the employer should pay the same wage to the workers of these two occupations.

term in this equation captures the change in the average wage of males (females) that would result from modifying the existing female proportion to the targeted level. The third term in this equation captures the part of the wage gap that reflects the difference in the proportion female coefficients between the two sex groups. It is important to stress that since the policy only changes quantities this third term is not supposed to be affected by the programme. The last term is fixed and may be seen as an "intercept" in this equation.

In order to calculate the effect of such policy using equation (81) one needs to choose the value of its only free parameter, $\overline{p_p}$. We have chosen four different levels for this parameter. The first corresponds to the lowest proportion of females among the occupational groups we have worked with (32% for the managerial group). The second simply respects the overall proportion of females in the formal labour force (39%). The third corresponds to the overall proportion of females in the entire labour force, which includes informal and self-employed workers (44%).[71]. The fourth level corresponds to the case where all establishments would have 50% females and males.

Table 21 presents the results of the decomposition displayed in equation (81) as well as the potential impacts of fixing the proportion of females across establishments at those pre-specified levels. Each column contains the results corresponding to one of those targets, which are displayed in row (1) of the Table. Row (2) displays the mean log wage gap, and row (3) the portion of the gap that is attributed to all variables but the proportion female one (i.e. the Δ of equation (81)). Rows (4), (5), and (6) respectively present the part of the gender wage gap that is associated with each of the first three components of equation (81). The percent contribution of each component to the overall gap is presented below each of these three rows. Row (7) shows the potential impact of the policies, that is, the summation of rows (4) and (5).[72] Row (7.a) displays the percent contribution of the policy to the overall gender wage gap.

The first point to notice from the results displayed in Table 21 is that increases in the targeted-level of the establishment female proportion tend to raise the impact of the policy (row (7.a)). The second point to notice is that as the policy target increases the contribution of the first component diminishes, whereas the contribution of the second component rises. These two points are a consequence of the facts that: (i) the wage/female-proportion relationship is much less steep for females than for males, and (ii) the large distance between the actual mean female proportion for males and females.[73] Another point to notice is that the magnitudes of the impacts are not negligible. For instance, taking the target of 44% - which is the proportion of women in the entire the labour force - the policy is capable of reducing the gender wage gap by 14.1%, which is approximately 1/7 of the gap. It is interesting to note that the magnitude of the policy impacts are similar to those found by Reilly and Wirjanto (1999a, Table 4). For instance, when imposing a establishment female proportion goal of 43%, the gender wage gap falls by 18.1% in Canada, a figure that is comparable to our estimated 14.1% when we impose a goal of 44%.

We may conclude from this admittedly crude exercise that there is some room to reduce

[71] This figure was taken from the National Household Survey (Pesquisa Nacional por Amostra de Domicílios) for the metropolitan area of Belo Horizonte in the year 2001.

[72] Recall that we are assuming that the coefficients will not change with the implementation of the policy, so the figures in row (6) should not contribute to the impact of the policy.

[73] The values of $\overline{p_m}$ and $\overline{p_f}$ are approximately 0.24 and 0.58 respectively, with $(b_{f,fem}, b_{m,fem}) = (-0.0891, -0.1975)$. Hence, higher policy-target levels tend to increase the impact of the programme, with policy targets closer to $\overline{p_m}$ ($\overline{p_f}$) making the contribution of the first component smaller (bigger) than the contribution of the second one.

Table 21: Decomposition of the Impact of Fixed Female Proportion Policies

Components	Policy 1 (A)	Policy 2 (B)	Policy 3 (C)	Policy 4 (D)
(1) - Target	32%	39%	44%	50%
(2) - Wage Gap	0.3571	0.3571	0.3571	0.3571
(3) - Delta	0.3536	0.3536	0.3536	0.3536
(4) - First Component	0.0153	0.0291	0.0380	0.0508
(4.a) - Percent (4)/(2)	4.3	8.2	10.6	14.2
(5) - Second Component	0.0227	0.0165	0.0125	0.0067
(5.a) - Percent (5)/(2)	6.4	4.6	3.5	1.9
(6) - Third Component	-0.0347	-0.0423	-0.0471	-0.0542
(6.a) - Percent (6)/(2)	-9.7	-11.8	-13.2	-15.2
(7) - Impact (4)+(5)	0.0380	0.0456	0.0505	0.0575
(7.a) - Percent (7)/(2)	10.7	12.8	14.1	16.1

Notes:
Row definitions: Row (1) Policy target for proportion of females across establishments; Row (2) Mean log wage gap between males and females; Row (3) Portion of the gap that is due to all covariates (including the intercept) but the establishment female proportion; Row (4) Effect of change in male mean establishment female proportion on the gap in row (2); Row (4.a) Percent contribution of row (4); Row (5) Effect of change in female mean establishment female proportion on the gap in row (2); Row (5.a) Percent contribution of row (5); Row (6) Effect of difference in coefficients for establishment female proportion on the gap of row (2); Row (7) Sum of rows (4) and (5); Row (7.a) Percent contribution of row (7).

the gender wage gap in Brazil through policies that try to reduce gender segregation at the establishment level. This does not mean that there are no other policies that can achieve similar or even higher reductions in the gender wage gap (e.g. comparable worth policies). But this investigation would require a proper cost-benefit analysis, a task that is beyond our objectives here.

10 Conclusions

In this paper we examine how the segregation of women across establishments affects the wages of males and females. To investigate this issue, we use a panel of matched employer-employee data from Brazil covering three years, 2000-2002. The data set is rich in both worker and establishment characteristics, and is based on administrative files maintained by the central government, which gather information provided by all registered firms in the country. Unique establishment and worker identification numbers allow the link of workers and establishments over time. Throughout this study we make use of various longitudinal models to assess the wage impact of establishment gender segregation. We also obtain cross-section estimates of these impacts, which are compared to the longitudinal results.

Our contributions to the literature are twofold: first, this is the first study that uses a panel of employer-employee matched data to investigate the effect of establishment gender composition on workers' wages; second, we have developed two models that are capable

of explaining the empirical results in terms of the signs that the effect of establishment female segregation may have on male and female wages.

Our results indicate that the effect of establishment gender segregation on wages seems to be negative for both gender groups. This negative sign is line with what has been previously found in the related literature. What seems different, however, is that this effect is stronger (i.e. more negative) for males than for females.

The comparison between the cross-sectional and the longitudinal results suggests that unmeasured, time-invariant worker- and establishment-specific effects are correlated with the establishment female composition, and thus the latter results differ substantially from the former ones. This implies that unmeasured characteristics matter for the understanding of the impact of gender segregation on the male-female wage differential. In addition, since the longitudinal model estimates are less negative than the cross-sectional ones, the unmeasured characteristics of workers and establishments seem to be negatively correlated with the establishment female proportion variable. A possible explanation for this negative correlation is that workers of both sexes with lower unmeasured skills tend to be sorted into plants with a largely female workforce. It could also be that unmeasured employers' efficiency level and discriminatory tastes towards females may explain this finding.

The Becker/Arrow model of employer discrimination was embedded in a monopsonistic framework so as to allow firms to pay different wages. Firms were assumed to be heterogeneous both in terms of productivity and tastes for discrimination. Under the assumption that there is a relationship between firms' productivity level and their degree of discrimination towards females, this model predicts various directions in terms of the signs that the relationship between the feminisation degree of firms and the wages of males and females can have. In particular, this model is compatible with the results that the gender composition effect is negative on female and males wages. The second model we have developed formalises for the first time in the literature the combination of the ideas proposed by the theories of statistical discrimination and quality sorting. Employers do not know the true productivity of individual workers and hold beliefs that, on average, females need to acquire more skills to work in skilled positions than males. Firms are heterogeneous in terms of their relative demand for skilled labour and workers incur costs to acquire skills. The model predicts that women (men) will be overrepresented in firms that demand relatively less (more) skilled labour, so the gender composition effect is negative on both male and female wages. These predictions are also compatible with ours and the literature's results.

Like other studies in the literature (e.g. Johnson and Solon (1986), Carrington and Troske (1998), and Reilly and Wirjanto (1999a)), the empirical findings of this study indicate that gender segregation at the establishment level accounts for an important part of the gender wage gap. This is supported by our decomposition results of the gender wage gap, which indicate that the contribution of the difference in the (mean) establishment proportion female between males and females is substantial. A simple simulation of the impact that an employment equity programme could have shows that the gender log wage gap would be reduced by around 1/7. It must be pointed out, however, that other policies could be more cost-effective in reducing this gap. But this analysis deserves further research, and is beyond the scope of this study.

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