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Tastes for discrimination in monopsonistic labour markets☆

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ABSTRACT

This paper presents a model where wage differences between men and women arise from taste-based discrimination, monopsonistic mechanisms and gender differences in compensating wage differentials. We show how preferences against women affect heterogeneity in firms' pay policies in the context of an imperfect labour market with non-wage amenities, deriving a test for the presence of taste-based discrimination and of compensating wage differentials. These results inform an analysis of sex pay differences in the Italian manufacturing sector, which shows that preferences for workplaces providing more flexible schedules are a significant determinant of the gender wage gap. Taste-based discrimination mechanisms appear to be significant as well, but small in size.

1. Introduction

Gender wage gaps are one of the most persistent economic regularities, on which many hypotheses have been formulated and, at least since the seminal work by Oaxaca (1973), many regression approaches have been proposed.[1] In this paper we combine elements of several of the existing theories, building a model where differences between men and women are determined by three main factors: *Becker-type* (or so-called taste-based) and *Robinsonian* (or so-called monopsonistic) discrimination, as well as gender differences in compensating wage differentials. Based on this theoretical framework, we develop empirical strategies that allow to test for the presence of these firm-level mechanisms driving the gender pay gap.

According to the theory of Becker (1957), taste-based discrimination arises because some employers have a dis-utility in working with women, so that either they are able to pay them less than their productivity, or they avoid hiring them, reducing the aggregate female labour demand. As a consequence, firms where discriminatory preferences are small enough can employ a given quantity of female workers at a lower wage than the one needed to hire the same quantity of men. Instead, *Robinsonian* discrimination is a mechanism arising when firms have monopsonistic power in the labour market. If the assumption of price taking behaviour is relaxed, employers minimize costs not only by adjusting quantities, but also by adjusting wages. In this context, according to the *Robinsonian* discrimination hypothesis, gender wage differences are driven by employers' greater monopsonistic wage-setting power against women, provided that, on average, the female labour supply to the firm is more rigid than the male one.[2]

Studying the impact of taste-based discrimination in the context of monopsonistic labour markets is an interesting choice for several reasons. First, from a theoretical perspective the two discriminatory mechanisms (employers' preferences and wage setting power) should not be considered as mutually exclusive. On this respect, Black (1995) and Flabbi (2010) build dynamic models where taste-based discrimination

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[1] See Blau and Kahn (2017) for a recent literature review on the main theories and existing evidences on the gender wage gap.

[2] The original model of monopsony dates back to the 1930s Robinson (1933), but interest on the relationship between the labour market structure and gender pay differences has emerged only more recently (see Boal and Ransom, 1997; Manning, 2003).

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itself produces monopsonistic discrimination against minority groups, showing that one of the two factors may even strengthen the other. Secondly, several studies, using different approaches in a variety of contexts, have documented the presence of some degree of employers' wage setting power and of substantial differences in the female and male labour supply elasticities to the firm.[3] Also from a more theoretical perspective, Boal and Ransom (1997) show that a monopsony is implied by standard dynamic search models in which larger firms face dis-economies of scale in hiring workers.

In this paper we show that a model of taste-based discrimination in which employers can set wages, employment levels, and gender-specific non-wage amenities provides interesting insights on the nature of sex differences in *firms' wage policies*. Such policies represent pay heterogeneity across employers conditional on workforce composition, and substantial gender differences in this wage component have been documented for several countries by a recent and growing literature (see in particular Bruns, 2019; Card et al., 2016; Casarico and Lattanzio, 2019; Coudin et al., 2018; Morchio and Moser, 2019; Sin et al., 2020). In our theoretical framework we show that, if tastes against women arise in the context of an imperfect labour market, even highly discriminatory employers hire female workers, but they offer them lower wages to compensate for the dis-utility associated to working with them. This outcome is different from the predictions of the original Becker's model, according to which all employers below a marginal level of discrimination prefer hiring women, while those above this threshold avoid employing them.

Given that in our theoretical model firms pay women below the monopsonistic benchmark more the stronger their prejudices, we show that workplaces' compensation policies estimated through AKM regressions Abowd et al. (1999) embed taste-based discrimination. We also discuss the role of monopsonistic discrimination and of gender differences in compensating wage differentials as additional components of the gender wage gap in firms' wage policies, deriving empirical tests for the presence of these mechanisms. In particular, we test three main hypothesis on the determinants of gender differences in firms' pay policies. First, we evaluate the importance employers' monopsonistic discrimination, relying on the fact that firms belonging to the same labour market, defined in terms of geographic- industry- and firm-size proximity, should face similar opportunities of marking down female wages more than male pay levels. Then, we test for the presence of taste-based discrimination and gender differences in compensating wage differentials using proxy variables for these two phenomena within a theoretically grounded regression framework. We approximate preferences against women adopting two commonly used measures, i.e. the presence of women at the top of the occupational hierarchy and the female employment share.[4] When testing for the presence of gender differences in compensating wage differentials, we focus on the role of flexible working schedules and use the availability of part-time work as proxy for work environments potentially preferred by women.[5]

The application of this paper is based on data covering the population of private sector workers in the Veneto region of Italy. We focus the analysis on manufacturing *local labour markets* only, since these can be considered groups of firms characterized by relatively homogeneous labour market structures.[6] First, we show that the gender gap in AKM firms' pay policies induces a large variability in the total gender wage gap. Firms where such pay premia are relatively less favourable for women are associated to substantial female wage penalties. Conditioning on observable characteristics, gender differences in returns to such characteristics, firm and worker fixed effects, the gender wage gap grows by up to 36% when moving from the bottom 20% to the top 20% of firms that pay relatively lower wage premia to women. Moreover, controlling for narrowly defined local labor market effects reduces this variability in the conditional gender wage gap by around one third. These results suggest that monopsonistic discrimination mechanisms are potentially relevant, but they also show that most of the variability in the conditional gender wage gap across firms occurs within narrowly defined labour markets, rather than across them.

Using a different regression approach we find that taste based-discrimination and gender differences in preferences for flexibility provide a small, but significant contribution to the firm-level gender wage gap. In particular a 10 percentage points increase in the female employment share within firms implies between 0.2 and 0.9 percentage points reduction in the pay gap, conditioning on workers' productivity and monopsonistic discrimination effects. The presence of women at the top of the corporate hierarchy, while determining around one percentage point increase in overall conditional gender wage differences, has no significant effects on the conditional level of female wages at the bottom of the firms' structure, a result consistent with the findings by Flabbi et al. (2019).

We also find that women earn relatively less at firms that offer more flexible working schedules. In particular, we document up to more than one percentage point growth in the gender wage gap conditional on employers' wage setting power and workers' productivity for each 10 percentage points increase in the share of total days worked part-time within firms. Thus, flexibility in working schedules appears to be a job characteristic preferred by women, which allows employers to reduce the female wage rate with respect to male pay levels.

Being able to distinguish among the sources of wage differences between men and women is not merely a theoretical exercise, but it has important implications on the choice of the most effective policies to implement in order to achieve greater equality. The approach developed in this paper can be helpful when testing the implications of Becker's theory in the data. Most of the existing contributions in this area face the challenge of finding a reliable firm-specific parameter for discriminatory preferences. Indeed, such information is sometimes explicitly available from surveys only at an aggregate level or in particular contexts (as for example in Charles and Guryan, 2008; Glover et al., 2017). More often, discriminatory preferences are approximated by the female share of workers within firms (e.g. Weber and Zulehner, 2014) and by the presence of women in executive boards or in the management (e.g. Cardoso and Winter-Ebmer, 2010; Flabbi et al., 2019; Gagliarducci and

[3] Among others, see Azar et al. (2020a); Barth and Dale-Olsen (2009); Depew and Sørensen (2013); Hirsch et al. (2010); Muehlemann et al. (2013); Ransom and Oaxaca (2010); Ransom and Sims (2010); Webber (2015, 2016) and, for Italy, Sulis (2011). All of these studies provide either indirect or direct support to the hypothesis of monopsonistic labour markets. Exceptions to this trend can also be found in the empirical literature, among which Matsudaira (2014), who provide support for the perfectly competitive hypothesis in the context of California's nursing home sector.

[4] The female employment share is a theoretically grounded proxy variable among firms facing a similar technology and labor market structure. Evidences on whether these two variables can be considered valid approximations for employers' tastes are not abundant. Homophily among managers is documented by Giuliano et al. (2009) and Giuliano et al. (2011), who find that managers' race characteristics tend to be correlated with the characteristics of new hires and promotions. Gagliarducci and Paserman (2015) also find that female managers are more likely to work at establishments where women-friendly policies are in place. Maida and Weber (2020) find instead that increased female representation in corporate board has only moderate effects on women's appointment to managerial positions. For what concerns the employment share of minorities, apart from theoretical considerations, evidences on its link to affirmative action policies are provided by Miller (2017).

[5] The availability of part-time work has been found to be an important determinant of female labour force participation (e.g. Del Boca, 2002) and it tends to be considered a desirable job characteristic by women (e.g. Booth and van Ours, 2013). Thus, it is intersing to study whether there are effects on female wages when more flexibility is available at a given workplace.

[6] Local labour markets (or *districts*) are geographical and economic entities that, in Veneto, are characterised by a high density of small-sized manufacturing-oriented firms. We have constructed them using a definition of the Italian national statistical office based on census' commuting data.

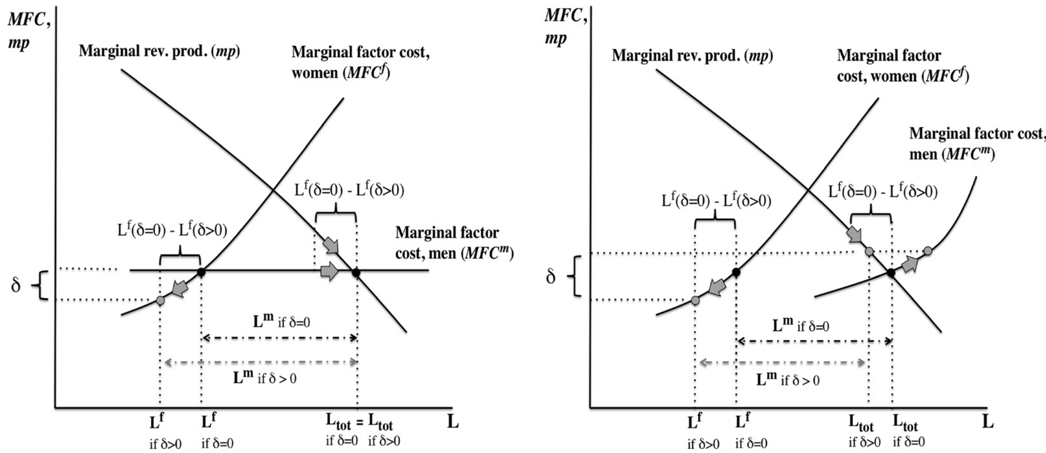

Fig. 1. Graphical representation of the model under different market structures and discrimination levels. (***a***) The equilibrium in the absence of taste based discrimination ($\delta = 0$) is represented by the black dots, where $mp = MFC^f = MFC^m$. If $\delta > 0$, female employment is reduced to the level $L^f(\delta > 0)$, represented by the grey dot where $mp - MFC^f = \delta$. Instead, mp and MFC^m are kept constant, which implies that the difference $L^f(\delta > 0) - L^f(\delta = 0)$ is compensated by an equivalent growth in male employment (L^m). (***b***) The equilibrium in the absence of taste based discrimination ($\delta = 0$) is represented by the black dots, where $mp = MFC^f = MFC^m$. The grey dots represent the optimal points on each of these curves when $\delta > 0$. At this equilibrium, female employment is reduced to the level $L^f(\delta > 0)$, represented by the grey dot on the MFC^f curve. As a consequence, mp grows above the curve MFC^m and more male workers are hired until mp and MFC^m are set equal again (grey dots on the respective lines). Since hiring more men is increasingly costly, the growth in male employment is smaller than $L^f(\delta > 0) - L^f(\delta = 0)$ (i.e. for fixed technology and supply functions, more discriminatory firms are smaller in size).

Paserman, 2015). Our contribution to this literature is to provide an empirical test on the relevance of these firm-level measures of taste-based discrimination, which is grounded on both, theoretical and empirical considerations.

The paper is organized as follows. Section 2 presents the theoretical model and Section 3 discusses its identification. Section 4 presents the data and Section 5 presents the main empirical results of the paper, while the final section contains the concluding remarks.

2. Theoretical framework

2.1. Profit maximization

We consider a static model where *Robinsonian discrimination* arises as the result of third degree price discrimination. Taste-based discrimination is defined as an employer-specific exogenous cost, which is proportional to the female employment level. In this model, an employer chooses a quantity of labour $L = L^m + L^f$ maximizing the utility profit function, which reads as

$$\pi(L^m, L^f) = pq(L) - w^m(L^m)L^m - w^f(L^f)L^f - \delta L^f \tag{1}$$

Throughout the paper, the subscripts m and f stand for male and female respectively. The parameter p is the output price and $q(L)$ is the production function, with $q' > 0$ and $q'' < 0$. Male and female workers are perfect substitutes in the technology. w^m and w^f are gender-specific inverse labour supply functions, which are increasing in L^m and L^f, respectively. Finally, δ is a taste-based discrimination parameter.

Under standard assumptions,[7] the first order conditions of profit maximization can be written as

$$mp = w^m\left(1 + \frac{1}{\epsilon^m}\right) \qquad mp = w^f\left(1 + \frac{1}{\epsilon^f}\right) + \delta$$

where mp is the marginal revenue product and ϵ^g is the elasticity of the labour supply for $g = m, f$. The solution of the model is graphically represented in Fig. 1, where the optimality conditions are characterized under different choices of the parameters. Namely, the left panel of the figure represents the solutions when $\epsilon^m \to \infty$ and $\epsilon^f < \infty$ for the cases of zero and positive taste-based discrimination, while the right panel describes the solutions when $\epsilon^g < \infty$ ($g = m, f$), again for the cases in which $\delta = 0$ and $\delta > 0$.[8]

In general, in this model wages are marked-down with respect to the marginal revenue product (mp), and this mark-down grows as the labour supply becomes more rigid. If $\delta = 0$ the marginal revenue product is set equal to each gender-specific marginal factor cost (MFC^g). When $\delta > 0$, there is a difference between mp and MFC^f in the case of women. In order to adjust for the cost of δ, the employer reduces female employment (L^f) and wage levels (w^f) below the monopsonistic benchmark and this reduction is compensated by only a less than proportional growth in male employment (L^m), as hiring more men is increasingly costly, unless the male labour supply is perfectly elastic.

To sum up, a monopsonistic employer for which $\delta > 0$ produces less output, hires fewer women, has a lower female share and pays women less than what would be observed at the monopsonistic benchmark (i.e. at $\delta = 0$). Another useful relationship is that, assuming $\delta < mp$, for fixed technology and labour supply functions a lower female share (thus also a higher δ) implies a higher ratio δ/mp.[9] This ratio can be considered an approximation of Becker's *generalised* discrimination coefficient, which he originally defined as the difference between actual female wages and those prevailing in the absence of taste-based discrimination, divided by the non-discriminatory wage rate. In our setting, given the presence of imperfect labour markets, mp does not exactly represent the prevailing wage rate in the absence of taste-based discrimination, while female wages are not marked down by exactly δ due to employers' prejudices.

[7] Two sufficient conditions for optimality are

$$2w^{g\prime} + w^{g\prime\prime}L^g > 0 \qquad \text{for } g = m, f$$

[8] For simplicity of exposition, we also assume that at the equilibria described in Fig. 1 the reservation wage of men and women (that is, the minimum wage required to attract at least one unit of female or male labour) are lower than the female (male) wage rate implied by the first order conditions.

[9] Assuming fixed technology and labour supply functions, $L^f(\delta = b) < L^f(\delta = a)$ and $L^m(\delta = b) > L^m(\delta = a)$ for $b > a \geq 0$, i.e. the female share is decreasing in δ. Notice that $mp(\delta = b) - mp(\delta = a) < (b - a)$, i.e. the growth in productivity induced by a growth in δ cannot be greater than the growth in δ (otherwise it would be profitable to hire more female workers, reducing productivity). Assuming $1 > b/mp(\delta = b)$ is then sufficient for the following inequality to hold $b/mp(\delta = b) > a/mp(\delta = a)$, since adding $b - a$ to the numerator and $mp(\delta = b) - mp(\delta = a)$ to the denominator of $a/mp(\delta = a)$ is a strictly increasing transformation.

Nonetheless, δ/mp is still a useful parameter to rank employers' according to the relative strength of their prejudices, as we discuss further in the next section.

When comparing any two actual firms, the relationships between firms' characteristics and employers' discriminatory preferences presented above do not necessarily hold, since each firm may have different labour supply functions and production technologies. For this reason, in the next paragraph we characterize employers' heterogeneity more explicitly.

2.2. The role of workplace heterogeneity

In this paragraph we characterize differences in wages across firms by introducing heterogeneity in employers' taste-based discrimination and wage setting power. We also introduce heterogeneity in individual labour productivity, by allowing workers to provide different contributions to firms' revenues. The next paragraphs further characterize the model by discussing the labour market structure and introducing gender-specific non-wage amenities.

Consider a population of firms indexed by j. We assume that each firm faces arbitrary gender-specific inverse labour supply functions, where the respective elasticities are denoted by ϵ_j^g. The functional form of these labour supplies is discussed below. For the time being, the first order condition of profit maximization can be written as

$$w_j^g = mp_j\left(\frac{\epsilon_j^g}{1+\epsilon_j^g}\right)\left(1 - 1[g=f]\frac{\delta_j}{mp_j}\right)$$

Notice that in the above equation δ_j is modelled as an employer-specific discriminatory parameter (i.e. taste-based discrimination varies across firms). This parameter can also be expressed as a percentage of the firm-specific marginal revenue product mp_j and, as discussed in the previous paragraph, the ratio δ_j/mp_j can be considered an approximation to Becker's *generalised* discrimination coefficient. In the remainder of the paper, we use this latter definition of discrimination in order to rank employers' prejudices.[10] With this approach, a given preference parameter δ_j is considered more discriminatory at firms that are relatively less productive - which, consequently, pay women proportionally less than men - with respect to firms having a higher marginal revenue product. For notational convenience, we define the following parameter

$$-\hat{\delta}_j \equiv \ln\left(1 - \frac{\delta_j}{mp_j}\right)$$

where $\hat{\delta}_j$ is monotonic and increasing in δ_j/mp_j, it is constant at the firm level and it approximates the percentage of labour productivity that is marked-down due to employer's prejudices.

We introduce individual heterogeneity in productivity by assuming that workers provide different amounts of equally productive units of labour l^i.[11] If employees are *endowed* with such heterogeneous quantities of labour, we can write worker i wage equation as a function of the firms' unitary pay level, that is

$$w_{ij} = l_i w_j^g = mp_{ij}\left(\frac{\epsilon_j^g}{1+\epsilon_j^g}\right)\exp(-\hat{\delta}_j 1[g=f]) \qquad mp_{ij} \equiv l_i mp_j$$

$$\Rightarrow \ln w_{ij} = \ln mp_{ij} + \ln\left(\frac{\epsilon_j^g}{1+\epsilon_j^g}\right) - \hat{\delta}_j 1[g=f] \tag{2}$$

According to the above equation, log wages are an additively separable function of workers' productivity, of firms' wage setting power and of employers' discriminatory preferences.

In order for this model to be considered realistic, we need to introduce the possibility of misspecifications, which could arise due to several firms', workers' or match wage components that we have not considered explicitly. Moreover, in the absence of information on employers' tastes, workers' productivity and firms' wage setting power, the above three elements can be estimated or controlled for only in a longitudinal setting. Thus, we also need to add dynamic considerations to our static framework. Before turning to these problems, in the next section we discuss more carefully the functional form of the labour supply to the firm.

2.3. The labour supply to the firm

According to Eq. (2), monopsonistic *mark-downs* of wages with respect to productivity have an influence on a worker's pay, unless we believe such mark-downs to be fairly close to zero.[12] In this theoretical framework we consider a special case of firms' wage setting behaviour, assuming that all employers operating in a given factor market face an inverse labour supply to the firm of the following form

$$w_j^g = (L_j^g)^{\alpha^g}(z_j^g)^{\gamma^g} \quad \Rightarrow \quad \ln w_j^g = \alpha^g \ln L_j^g + \gamma^g \ln z_j^g \tag{3}$$

In the above equations, w_j^g is the firms' wage paid to each productive unit expressed in levels, z_j^g is a vector of characteristics and a residual term, γ^g is a vector of parameters and a constant, L_j^g is the total amount of *productive units* supplied by gender g at firm j and α^g is a real-valued parameter. For the time being, we consider α^g to be only gender-specific. However, in Section 3.2, by providing a more precise definition of labour markets, we explicitly model heterogeneities in this parameter across firms.

The characteristics included in the vector z_j^g control for all factors determining heterogeneities in availability of productive units in the labour market, as long as they have an influence on wages. As we discuss further in the next paragraph, z_j^g can include firm-specific non-wage amenities that are preferred by a given gender group. In this setting, the parameter $1/\alpha^g$ becomes a measure of the elasticity of the labour supply faced by firms, net of any other composition effect influencing the wage-size relationship.

The labour supply function just described has two convenient features. First, for any two firms s and j facing the same factor market structure

$$\epsilon_j^g = \epsilon_s^g = \frac{1}{\alpha^g} \qquad \forall\, s \neq j$$

That is, the elasticity of supply is a constant parameter across such firms. Secondly, provided that (3) is an appropriate functional form specification, monopsonistic mark-downs in Eq. (2) are not only additive, but also independent of employment levels,[13] so that worker's i wage equation becomes

$$\ln w_{ij} \approx \ln mp_{ij} - \alpha^g - \hat{\delta}_j 1[g=f] \tag{4}$$

An useful implication of these two properties is that, whenever firms face the same factor market structure, gender-specific monopsonistic mark-downs can be controlled for in a regression framework by simply adding fixed effects for each of these labour markets. However, this approach

[10] Notice that for a constant labour supply and technology, there is a monotonic and positive relationship between δ_j and δ_j/mp_j as long as $\delta_j < mp_j$. See the discussion in footnote [9].

[11] A richer modelling choice would be to assume imperfect substitutability of workers in the firm's technology along some dimension. We do not consider this extension of the model explicitly, but, in the application (Section 5.3), we test our main results using also a more nuanced empirical specification, where the unit of analysis are specific jobs within a firm (thus, a specification where imperfect substitutability is allowed for different jobs within a workplace).

[12] Sulis (2011) provides a direct assessment of the amount of labour market power held by firms in the Italian private sector, which is the market considered in the application, showing evidences consistent with the presence of this mechanism and of relevant gender differences in the elasticity of the labour supply to the firm.

[13] In particular, notice that for all firms j in a given labour market

$$\ln\left(\frac{\epsilon_j^g}{1+\epsilon_j^g}\right) = \ln\left(\frac{1}{1+\alpha^g}\right) \approx -\alpha^g \qquad \forall j$$

is feasible only if the functional form of Eq. (3) is reasonable and if sets of firms facing an approximately similar gender-specific labour supply function can be identified.

It is worth noticing that Card et al. (2018) present a similar model of monopsonistic wage setting, where a log-log functional form of the labour supply to the firm is derived from specific assumptions on workers' indirect utility. They show that a simple two-period extension of the model has similar implications in steady state to this static framework and leads to random mobility of workers across firms. Nevertheless, we stress that this conclusion is reached in a simplified framework, where important considerations, such as workers' job switching costs, are not taken into account.

2.4. Compensating wage differentials

Given a labour supply of the form provided by Eq. (3), it is natural to model non-wage amenities as firms' characteristics that are included in z_j^g. These characteristics can be potentially different by gender in their level and in their influence on the wage rate. In analysing the role of these firm characteristics, for simplicity we assume that only women value a given non-wage amenity. Let dw_j^f represent the reduction in the unitary female wage rate provided by this job characteristic, which we assume to be constant for any given quantity of female employment.[14] Notice that if a firm becomes endowed with such non-wage amenity without incurring in any cost, then the female wage rate reduces by dw_j^f, and it becomes optimal to hire more female workers until the following profit maximization condition holds

$$\ln\left[w_j^f(dw_j^f=0)-dw_j^f\right]=\ln mp_j-\alpha^f-\hat{\delta}_j \tag{5}$$

In the above equation, $w_j^f(dw_j^f=0)$ is the female wage rate that would prevail in the absence of the job characteristic preferred by women. The consequence of becoming endowed with the non-wage amenity is that female wages become lower than their initial optimal level. Hiring more female labour induces a growth in female wages net of non-wage amenities ($w_j^f(dw_j^f=0)$) and a reduction in the marginal revenue product (mp_j), until the condition provided by Eq. (5) holds.[15] The reduction in mp_j also induces a reduction in the optimal male wage rate by the same amount, which is achieved through a corresponding reduction in male employment. Thus, for a given technology and labour supply elasticity to the firm, female-specific non-wage amenities that can be provided without costs have no influence on the gender wage gap at the firm level in this model. Indeed, they only affect sorting, increasing the share of women, while reducing male and female wages by the same amount.

A richer modelling choice is to consider the non-wage amenity's production as part of the profit-maximization problem faced by employers (i.e. as an endogenous job characteristic influencing also the labour demand). For clarity of exposition, we begin by assuming that the marginal cost (i.e. cost per female labour unit) of producing the non-wage amenity is constant and equal to c. If $c>dw_j^f$, then it is not feasible to produce this job characteristic, as it costs more than the reduction in the female wage rate that it provides. If $c\le dw_j^f$, then firms find it profitable to produce the non-wage amenity. The resulting optimal female wage rate is given by the following condition

$$\ln\left[w_j^f(dw_j^f=0)-dw_j^f+c\right]=\ln mp_j-\alpha^f-\hat{\delta}_j \tag{6}$$

which is similar to the one described for the case of an exogenous job characteristic. However, there is now a wedge between actual female wages, given by $\ln\left[w_j^f(dw_j^f=0)-dw_j^f\right]$, and the RHS of the optimal condition in Eq. (6). This implies that female employment and wage growth is lower than the one occurring in the case of amenities that are not produced. Moreover, if we take the difference between male and female predicted wage schedules, there is an additional component of this difference that is attributable to c, the marginal cost of producing the job characteristic preferred by women. Thus, producing a costly non-wage amenity preferred by women has an influence not only on sorting, but also on the gender wage gap at the firm level.

This reasoning can be easily extended to the case of decreasing returns to scale in the cost of the non-wage amenity. Condition (6) would still hold, but the marginal cost c would grow together with employment and female wages. In the case of increasing returns to scale, i.e. if the average cost c reduces with female employment, then there could also be equilibria where a firm for which $c>dw_j^f$ at the optimal production level without the non-wage amenity finds it profitable to produce it. This would depend on whether the marginal cost decreases fast enough with employment levels, so that the optimal point provided by Eq. (6) becomes feasible.

3. Empirical specification of the model and identification

3.1. Firms' wage policies and their estimation

In this section, we show how the wage equation derived in the theoretical framework relates to the two-way fixed effects (or AKM) regression model Abowd et al. (1999), discussing the main assumptions required for its consistent identification. For this purpose, we introduce additional components to Eq. (4), allowing for the presence of measurement error and model misspecifications. Moreover, we take into account dynamic considerations, including in the model innovations in workers' productivity as well as in other unobserved wage components, but also introducing some restrictions on these time-varying processes.

We define ρ_j^m and ρ_j^f as *time-constant, gender-* and *employer-specific* residual terms, representing firms' deviations from the predicted wage schedule defined by Eq. (4). Such deviations can be attributed to several factors usually linked to heterogeneity in compensation policies across workplaces (see Card et al., 2018 for an overview of the main arguments). In particular, as discussed in Section 2.4 these deviations can be linked to compensating wage differentials. Other mechanisms may include efficiency wages, wage posting, employers' rent-sharing policies, and measurement error. Notice that, even if ρ_j^g is gender-specific, part of the above mentioned mechanisms could also equally affect men and women within firms.

We define r_{it} as an *individual-specific* and *time-varying* wage residual (where t denotes discrete periods), which we assume to be normally distributed with mean zero in the population and independent from all the other wage components. Adding these elements to the wage equation, we have a model that reads as

$$\ln w_{ijt}=\ln mp_{ijt}\underbrace{-\alpha^g-\hat{\delta}_j 1[g=f]+\rho_j^g}_{\equiv\omega_j^g}+r_{it} \tag{7}$$

As can be noticed by the time index, workers' productivity is allowed to change across periods and, as discussed below, we assume that it can be approximated correctly by unobserved time-constant and observable time-varying individual characteristics. In this setting, the element ω_j^g defined in Eq. (7) can be interpreted as a time-constant firm wage residual. Throughout the paper, we call this residual *firm wage policy*, or *firm wage premium*.

Under assumptions on the error term r_{it} that are discussed below, the identification of compensation policies ω_j^g can be achieved by estimating an AKM regression model separately by gender. In particular, let $j=\iota(i,t)$ index the firm in which worker i is employed at time t. Assume that employees are observed for T time periods and let W_i represent a $T\times 1$ vector of daily wages, while X_i a $T\times P$ matrix of time-varying

[14] This assumption simplifies the presentation of the results, but it can be relaxed by letting dw_j^f change with employment levels or by assuming non-constant returns to scale in the production of the non-wage amenity.

[15] Notice that $\ln\left[w_j^f(dw_j^f=0)-dw_j^f\right]$ is the observed female wage rate for a firm that possesses the non-wage amenity.

individual characteristics. Then, the two-way fixed effects model can be specified as follows

$$\ln w_{it} = x_{it}\beta + \eta_i + \omega_j^g + r_{it} \tag{8}$$

where w_{it} and x_{it} are rows of W_i and X_i respectively, β is a $P \times 1$ vector of parameters, while ω_j and η_i are respectively firm-constant and time-constant components of individual wages, which are allowed to be arbitrarily correlated with any of the characteristics in x_i, and which could be not perfectly observable.[16] In the application, we have adopted a specification of the model suggested by Card et al. (2018), including as covariates in x_{it} a cubic polynomial of age interacted by three occupation dummies, a dummy for fixed-term contracts and a full set of year fixed effects.[17]

The main assumption required for a consistent identification of the parameters in (8) is the absence of correlation between the error term r_{it} and all the other time-varying and (unobserved) time-invariant characteristics included in the model (Abowd et al., 1999; Card et al., 2013). This condition must hold also for error terms in periods different from t, so that, for example, mobility towards employers with given firm wage policies cannot be correlated with previous idiosyncratic shocks in earnings (this assumption is often labeled *exogenous mobility*).

Two relevant components entering in r_{it} are innovations in workers' unobserved earning abilities and job match effects associated to given employer-employee pairs. In the context of the model of Section 2.2, match effects could be interpreted as productivity shocks, like innovations in the parameter l^i that are not predicted by the time-varying controls included in x_{it} and that are associated to a match with a given firm j. They could also represent systematic differences in firms' wage policies associated to given worker-employer pairs, which would then enter in the residual term r_{it}.

As in Card et al. (2013), we assume that innovations in workers' unobserved earning abilities have mean zero and contain an unit root, while job match effects have mean zero for all i and j in the sample interval. Section A.1 presents some tests on the credibility of these restrictions on r_{it} along the lines suggested by Card et al. (2013) and Card et al. (2016). Moreover, we provide a sensitivity analysis on our main empirical results, by allowing firm fixed effects ω_j to be specific for manual and non-manual workers within workplaces.

The AKM regression model has been subject to an intense scrutiny in the recent literature. On one hand, research has been ongoing in developing empirical methods that impose less restrictions on workers' mobility (e.g. Abowd et al., 2019; Bonhomme et al., 2019). On this respect, in the Appendix we provide some supportive evidence on the reliability of the standard AKM assumptions.[18] Recent research on Italian administrative data conducted by Di Addario et al. (2021) provides further indirect support on the exogenous mobility assumption. In particular, this work uses an augmented AKM regression on hiring wages, designed to simultaneously estimate origin and destination effects. Results show that hiring wage variability is not explained by origin effects for both men and women, which suggests that, in the Italian context, match specific heterogeneity is not predictive of hiring wages at firms to which a worker moves. Thus, while potentially problematic, the exogenous workers' mobility assumption does not appear to be too restrictive in the labour market considered in the application of the paper.

Another criticism that has been raised with reference to the AKM model concerns its ability to actually identify the components of the wage variance that are attributable to firm wage policies, worker heterogeneity and sorting. A shown by Kline et al. (2020) using the dataset that is employed in the application of this paper, the variance of standard AKM worker- and firm-effects is upward biased, while their covariance is downward biased. As a consequence, measures of the model fit are also upward biased. Similar evidence is also documented at the cross-country level by Bonhomme et al. (2020). Notice however that the regression models proposed in this paper rely only on first moments of the parameters estimated through the AKM procedure. As a consequence, provided that the exogenous workers' mobility assumption is satisfied for both men and women, the standard AKM firm fixed effects represent an unbiased estimate of the true parameters of interest.

3.2. Gender gap in firms' wage policies, taste-based discrimination and compensating differentials

In this section, we discuss the identification of employers' discriminatory tastes and of gender differences in compensating wage differentials, which is based on the gender gap in firms' wage policies. Since firms' premiums are influenced also by the degree of labour market power held by employers, which could differ by gender, we begin by considering more explicitly the role of heterogeneities induced by monopsonistic mechanisms.

Following the discussion of Section 2.3 and adopting a similar notation, we assume that each firm belongs to a given labour market k. For each of them, we assume that employers face market- and gender-specific log-log inverse labour supply functions that read as

$$\ln w_j^g = \alpha_k^g \ln L_j^g + \gamma_k^g \ln z_j^g \qquad g = m, f \quad k = 1, \dots, K$$

where w_j^g is the unitary wage and the vector z_j^g contains unobserved characteristics affecting the labour supply (including non-wage amenities) and an error term. Given this functional form, it follows that the labour supply elasticity to the firm is determined by the constant parameter α_k^g only. This model also implies that the gender gap in firms' wage residuals can be written as

$$\omega_j^m - \omega_j^f \approx \hat{\delta}_j + \underbrace{\alpha_k^f - \alpha_k^m}_{\equiv \alpha_k} + \underbrace{\rho_j^m - \rho_j^f}_{\equiv \rho_j} \tag{9}$$

where $\hat{\delta}_j$ approximates Becker's generalised discrimination coefficient. Instead, the composite error term ρ_j reflects *heterogeneities* in residual firm wage components, as long as they affect differently men and women within the same workplace.

If the AKM assumptions discussed in the previous section hold, so that ω_j^g is identified consistently for both gender groups, we can consider Eq. (9) as a valid regression model. In this setting, a quantification of taste-based discrimination could be recovered by conditioning for market-constant effects α_k and firm level residuals ρ_j. However, since both of these confounding factors are mostly unobservable, a feasible alternative to this approach, which is followed in Section 5.3, is to test whether reasonable *proxy variables* for preferences against women (or for other potential mechanisms contributing to ρ_j) are significant predictors of the LHS of Eq. (9).

In our empirical specification, we have considered two proxy variables for $\hat{\delta}$, namely the presence of women at the top of the firm hierarchy and the share of female labour within firms. Both variables are usually associated to taste-based discrimination in the empirical literature. Regarding the influence of women at the top of the corporate structure, Gagliarducci and Paserman (2015) find that in Germany female managers are more likely to work in female-friendly firms. Similarly, Cardoso and Winter-Ebmer (2010) and Flabbi et al. (2019) show that the gender wage gap tends to be lower at women-led companies.[19]

[16] We implicitly maintain that the regression model is estimated separately by gender, so that each parameter should be considered gender-specific. For notational convenience, we have omitted the subscript g whenever redundant.

[17] Following Card et al. (2018), we normalize the age profiles to be flat at 45 years old.

[18] For example, in our setting the importance of match-specific wage effects appear to be limited in explaining earnings' variability, when compared with the model fit with additive firm and worker fixed effects.

[19] In the context of racial discrimination, two papers documenting the presence of homophily among managers are Giuliano et al. (2009) and Giuliano et al. (2011). Instead, other evidences that consider the representation

The female share of employment is typically considered a proxy of preferences against women as well (see for example Weber and Zulehner, 2014) and its growth has been linked to the presence of affirmative action policies (e.g. Miller, 2017). Moreover, this variable is associated to discrimination in the traditional model of Becker (1957). In the context of our theoretical framework, as discussed in Sections 2.1 and 2.2 a lower female share is linked to greater $\hat{\delta}_j$ conditional on firms' technology and on the labour market structure. Thus, to the extent that both factors are controlled for in a regression model, women's employment share within firms can be considered a valid proxy for taste-based discrimination also in our framework.

The regression model provided by Eq. (9) can be used to test also for the presence of a gender gap in compensating wage differentials. Women could indeed be more attracted by given amenities provided by employers, and as discussed in Section 2.4 this tendency can potentially affect ρ_j. Indeed, workplaces providing costly non-wage amenities to women are able to lower female pay levels with respect to the wage schedule predicted by workers' productivity, monopsonistic and taste-based discrimination. In the application, we have tested whether employers more willing to provide flexibility in working schedules are paying women less due to hedonic considerations.[20] This is a particularly interesting mechanism, given that part-time work is a relatively scarce resource in the labour market considered in the application, while its availability has been shown to improve female labour force participation (see in particualr Del Boca, 2002). For these reasons, we have included in our empirical model a control for the share of part-time employment within firms.

Section 5.3 further discusses the regression model implied by Eq. (9), presenting more details on the model specification, on the main assumptions required by several alternative estimators for the parameters of interest, and commenting on the results.

4. Data and sample selection

In the application of the paper, we rely on Italian linked employer-employee data from administrative sources (Veneto Working History database, hereafter VWH).[21] In particular, we study the population of private sector workers in Veneto during the period between 1996 and 2001.[22] Veneto is an important region of Italy, which represents around 10% of the national GDP. It is a manufacturing-oriented economy and it can be considered as a self-contained labour market, given its relatively limited out-migration.

The data is derived from INPS (National Social Security Institute) social security archives, which cover the population of private sector dependent workers, excluding self employed and public-sector employees. All firms registered at one of Veneto's INPS offices are included in the data,[23] which provide demographic and occupational information on their entire workforce and the location and the sector of activity of each company.[24] Workers who transit from these firms are observed also if they are employed by a private-sector employer outside of Veneto.

Table 1
Mobility of workers across local labour markets (1996–2001).

Industry	Number of worker-SLL-industry pairs	% Observed out of SLL-industry	% Changing firm	% Observed out of SLL-industry among workers changing firm
Manufacturing	828,969	23.3	50.6	47.3
Other sectors	811,969	23.9	51.6	45.3

The data provides information on gross daily wages, which are inclusive of all pecuniary benefits paid by employers. We have excluded part-time workers and apprentices from the analysis, as this choice limits the measurement error in actual time worked and it eases the comparison of firms' wage policies by gender. We have selected one job spell per individual in each year, choosing the longest work episode whenever a person was simultaneously employed at more than one firm. We have also restricted the analysis on firms belonging to the male or female largest connected sets, i.e. the set of all establishments connected by the mobility of workers, which is a relatively standard procedure in the literature (see for example Card et al., 2013).[25]

We have estimated the AKM model separately by gender on the entire sample of workers defined above. Results derived from the AKM regression are presented in the Appendix. We have then analysed the gender wage gap in firm wage policies on a more homogeneous group of firms, adopting further sample selection criteria based on firms' geographical location, product market structure and gender composition.[26]

Taking advantage of the comprehensive level of detail in the available data and exploiting also the peculiarities of Veneto, we have considered only firms belonging to one of the region's *local labour markets*. Such geographical entities (also called *districts*) were identified using the official classification of the Italian statistical office (ISTAT), which calls local labour markets *Sistemi Locali del Lavoro*, or SLL. Using data on individual commuting habits derived from the census, such SLLs are constructed as a group of municipalities that are highly connected in terms of employment.[27] A map of SLLs within Veneto and its neighbouring regions is provided by Fig. 2.

Table 1 shows that SLLs provide a relatively good approximation of a firm's labour market structure, as employers belonging to the same district tend to hire from the same pool of workers. As can be noticed, considering the period 1996–2001, only around 23% of workers employed in a given SLL are observed working also outside of this geographical area or in a different industry, where sectors are broadly defined considering manufacturing and non-manufacturing activities. When this proportion is computed considering only the population of workers who switched job during the period of observation, less than 50% of these employees are observed changing their SLL or their industry.

of women in corporate boards find weaker support for the presence of positive spillover effects on female workers (see Bertrand et al., 2019; Maida and Weber, 2020).

[20] On this aspect Booth and van Ours (2013) show that married women tend to prefer part-time contracts in the Dutch labour market.

[21] The VWH dataset has been developed by the Department of Economics of the University of Venice Ca' Foscari under the supervision of Giuseppe Tattara.

[22] The VWH data covers also less recent years, up to the 1970s. However, we have decided to restrict the sample to the most recent period covered by the data since female labour force participation has been steadily growing during the 1980s and early 1990s. Moreover, part-time contracts were introduced only in the mid-1980s, and their adoption has been staggered in subsequent years. These secular process could generate selection mechanisms across time that would make more difficult to disentangle different components of the gender wage gap, and they reduce the possibility of studying flexible working schedules in earlier years of the data.

[23] Such registration is compulsory for firms hiring dependent workers.

[24] According to the ISTAT census, in 2001 there were only 1.08 establishments for each firm in Veneto. Thus, the presence of multi-plant activities is quite limited in our data.

[25] The largest connected set corresponds to around 98% of the observations. See Abowd et al. (2002) for a discussion of this procedure and a more detailed definition of connected sets.

[26] The choice of estimating the AKM regression on the full database, restricting the sample only afterwards is adopted in order to measure firm wage policies with higher precision. Indeed, as shown by Andrews et al. (2008), measurement error in firms' wage policies reduces as the number of observable job mobility episodes increases.

[27] The connectivity of each group of municipalities is maximized considering two main measures: *i*) the proportion of jobs within the districts held by its residents and *ii*) the proportion of residents that work in the local labour market. See Lorenzini (2005) for the details of this procedure.

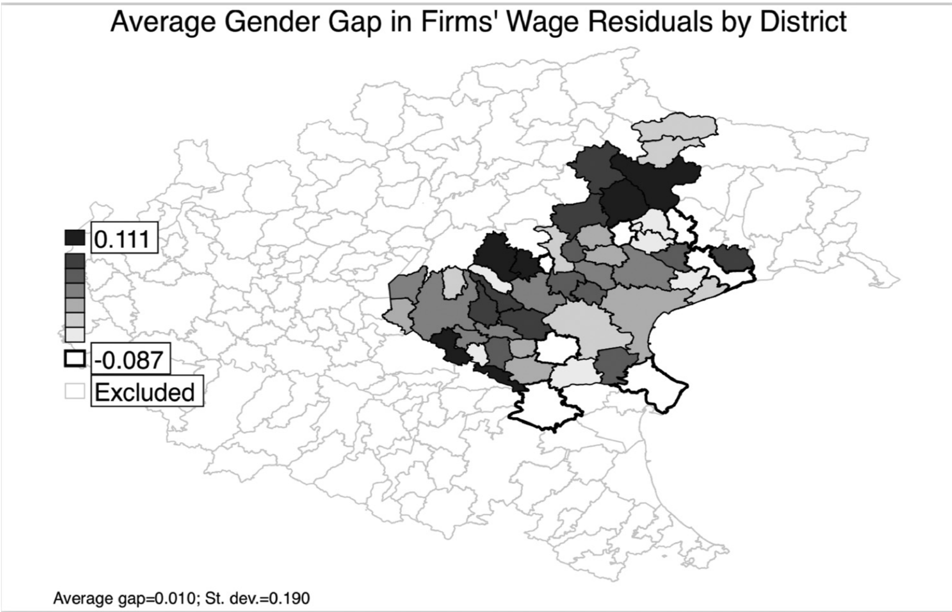

Fig. 2. Gender gap in firms' policies by local labour market. The gender wage gap in firms' policies is computed as the difference between standardized male and female employer effect estimated through an AKM regression model. It represents the percentage wage gain (or loss) experienced by women at a given firm, with respect to the gender gap in employers' policies observed in the restaurant sector. The sample is composed of 11,740 gender-balanced manufacturing firms selected along the lines discussed in Section 4. All averages are computed over firms, without weighting for their size.

Table 2
Workforce composition and gender wage gap by sector (1996–2001).

Number of observations			Conditional gender wage gap		
Gender	Manufacturing	Other	Independent Var.	Coefficient	S.e.
Male	2,011,273	1,437,580	Male worker	0.166	0.003
Row %	58.3%	41.7%			
Female	941,872	881,630	Male worker × Manufacturing	0.031	0.004
Row %	51.7%	48.3%			
Total	2,953,145	2,319,210	**N. Observations**	5,272,355	
Row %	56%	44%			

Descriptives by Gender, Manufacturing and Non-Manufacturing Sector

	Men			Women		
Variable	*Manuf.* *Mean (St. dev.)*	*Non-manuf.* *Mean (St. dev.)*	Diff.	*Manuf.* *Mean (St. dev.)*	*Non-manuf.* *Mean (St. dev.)*	Diff.
Log wage	4.885	4.908	**	4.626	4.735	**
	(0.341)	(0.443)		(0.277)	(0.352)	
Age	35.5	37.2	**	33.2	33.9	**
	(9.59)	(9.92)		(9.06)	(9.14)	
Firm size	242.8	562.3	**	302.2	719.9	**
	(626)	(1276)		(825)	(1362)	
Fixed-term	4.7%	5%	**	6.2%	11%	**
Manual workers	79.2%	65.7%	**	73.7%	41.6%	**

The conditional gender wage gap is estimated by a regression model that includes a quadratic age polynomial together with occupation, year and firm fixed effects. Standard errors are clustered at the firm level.

We have studied the gender wage gap further restricting the sample to manufacturing firms only.[28] This choice allows us to focus on a sample where heterogeneity in the labour and product market structure within narrowly defined industrial districts is arguably more limited. Indeed, the Italian region under analysis (Veneto) is characterized by a large number of small and manufacturing-oriented firms, which tend to be located in the same areas of the region, forming high-density conglomerates that specialize in narrowly-defined activities. Thus, manufacturing firms within local labour markets tend to be quite similar in terms of product and labour market structures. They also employ a large proportion of Veneto's workforce. The top-left panel of Table 2 shows indeed that around 56% of our sample is employed at manufacturing firms and that this proportion is relatively high for both, men and women.

As can be noticed from the top part of Table 2, skills demanded (thus workers hired) by manufacturing firms tend to be more homogeneous. Indeed, the proportion of manual workers and of fixed-term contracts is more similar between men and women in the manufacturing sector than in the non-manufacturing one. Such more limited heterogeneity can be noticed also from an analysis of workers' pay. The standard deviation of log daily wages is 0.34 in the manufacturing sector, while it is 0.43 in other industries. The same pattern holds for both, men (0.34 and 0.44) and women (0.28 and 0.35). Nonetheless, the gender wage gap, even when conditioned on standard controls for human capital, is higher in the manufacturing industry. The top-right panel of Table 2 shows indeed that the conditional pay gap between men and women is 3% higher at manufacturing firms.

As a final step, in order to further limit the bias in the measurement of firm wage policies, we have considered only companies where at least 15% of full-time workers employed during the period 1996–2001 were either men or women (we refer to these companies also as *gender-*

[28] We have excluded from the analysis also one very marginal sector, tobacco. For this industry, only one firm was observed in the final sample.

Table 3
Descriptive statistics by gender in the selected sample.

	Women		Men	
	Mean	*St. Dev.*	*Mean*	*St. Dev.*
Log wage	4.664	0.280	4.898	0.375
Age	33.6	9.2	35.6	9.5
Tenure	6.6	6.9	6.7	6.8
Firm size*	380.7	882.3	343.1	806.7
Fixed-term	6.8%		4.8%	
Blue collar	70.8%		74.1%	
White collar	29.1%		24.2%	
Manager	0.1%		1.7%	
N. firms	11,740		11,740	
N. workers	166,042		235,582	
N. observations	597,749		837,864	

*: Firm size is computed as number of full-year equivalent workers (total days worked in a year by a gender group within the firm, divided by 320).

balanced firms). Table 3 summarizes the main characteristics of the workforce by gender, considering only employees in the secondary sector, working in Veneto's local labour markets and at a gender-balanced firm. As can be noticed, the raw gender wage gap is of about 23%. Moreover, women are slightly more likely to work in clerical occupations and at larger firms, and they are younger, over-represented among fixed-term contracts and less likely to be managers. However, most of these differences are relatively small in magnitude.

5. Empirical results

5.1. Descriptive evidences on the firm-specific gender wage gap

We have estimated the AKM regression model presented in Section 3.1 separately by gender on the entire population of Veneto's private sector workers, considering the six-years period between 1996 and 2001. The details of the AKM regression estimation approach and its results are provided in Appendix A. In analysing the gender wage gap in firms' pay policies, we now consider only gender-balanced manufacturing firms, selected along the lines discussed in Section 4.

In this section, we provide evidences on the size of gender differences in firms' wage policies estimated through the AKM model. We first make employers' compensation policies comparable between men and women by expressing them as deviations from the (gender-specific) average firm's wage residual of a reference group. Following a common practice in the literature (e.g. Coudin et al., 2018) we choose the restaurant and accommodation sector to be the reference group.[29] As a result of this standardization choice, the gender gap in firms' pay policies can be interpreted as the difference between how much male workers are rewarded at a given workplace with respect to the male average firm premium in the restaurant sector, and how much instead female workers within the same firm are rewarded with respect to the average female firm premium in the restaurant sector. Notice however that this is a *relative* measure of sex pay differences. Indeed, even if, in principle, all firms could be on average highly discriminatory toward women or not, this information cannot be recovered using this method.

Adopting the notation introduced in presenting the empirical specification of our model, let ω_j^g represent the (standardized) firm wage policy of gender g at firm j. Fig. 2 provides the average gender gap in firms' wage policies ($\omega_j^m - \omega_j^f$), computed without weighting for employers' size in each of Veneto's local labour markets. As can be noticed, the average level of $\omega_j^m - \omega_j^f$ across districts ranges between -0.08, that is, an average reduction of 8 percentage points in the gender gap in firms' policies with respect to the one observed in the restaurant sector, and 0.11. Moreover, even if with some exceptions, districts located toward the northern and more mountainous parts of Veneto tend to be darker in colour, i.e. they provide less favourable working conditions to women.

5.2. Quantification of the firm-specific gender wage gap and of its market-specific components

We now discuss a regression-based method that allows to measure the size of the firm-specific conditional gender wage gap. In this approach, we define a set of employers that, according to the metric given by $\omega_j^m - \omega_j^f$, provide less favourable working environments for women. In an alternative specification, we also consider the variable $\omega_j^m - \omega_j^f - \alpha_k$ to define less favorable firms for women, where α_k is a market-constant effect.[30] This alternative metric is estimated as the residual of a regression of $\omega_j^m - \omega_j^f$ on local labour market fixed effects interacted by two-digits (ISIC) sector fixed effects, three firm size dummies, a dummy for firms with an above-median composition of young workers, and a dummy for an above-median composition of manual workers.

Following this approach, we consider the cumulative distribution function (over firms) of $\omega_j^m - \omega_j^f$ (or $\omega_j^m - \omega_j^f - \alpha_k$), which we denote by F(), in order to define quintiles of increasingly less favorable firms for women. Then, using a human capital wage equation with worker and firm fixed effects, we evaluate the marginal effect on wages of being a men employed in one of the firms in the right tail of the distribution F(). More precisely, we estimate the following regression model

$$\ln w_{it} = b_m 1[g=m] + \sum_{\theta=\{0.2,\,0.4,\,\dots,\,0.8\}} b_\theta T_\theta + \beta x_{it} + \gamma 1[g=m] x_{it} + \eta_i + \phi_j + e_{it} \tag{10}$$

where w_{it} is worker's i wage at time t, η_i is a worker fixed effect, ϕ_j is a firm fixed effect (common for both gender groups), x_{it} is a vector of controls for observable individual characteristics (age cubic polynomial, tenure quadratic polynomial, three occupation fixed effects, a fixed effect for open-ended contracts, and a full set of year fixed effects) and e_{it} is an error term. We interact all the variables in x_{it} with the gender dummy $1[g=m]$, in order to control not only for human capital characteristics, but also for sex differences in the returns to such characteristics.[31] The coefficients of interest in the above model are the b_θ, which are associated to T_θ, an indicator variable that we define as

$$T_\theta = 1[g=m] 1\left[\theta + 0.2 \geq \mathrm{F}(\mu_j) > \theta\right]$$
$$\mu_j = \left\{ \omega_j^m - \omega_j^f \omega_j^m - \omega_j^f - \alpha_k \quad \theta = \{0.2,\ 0.4,\ \dots,\ 0.8\} \right.$$

where θ is a given percentile of the distribution F(). Thus, b_θ can be interpreted as the marginal effect on men's wages of working in the θ quintile of the distribution $\omega_j^m - \omega_j^f$, with respect to being employed in the quintile of the most favourable female firm wage policies as compared to the male ones. This marginal effect is estimated conditioning on observable individual characteristics, gender differences in returns to such characteristics, time-constant indivdual heterogeneity and a gender-constant firm fixed effects.

When the metric $\omega_j^m - \omega_j^f - \alpha_k$ is adopted in defining less favourable working environments for women, we condition on all factors influencing the average gender gap in firms' pay policies across markets, i.e. we use only the within-market variation of the gender gap in firms' pay

[29] In all regression models presented in the current and in the following section, the choice of the reference group has no effects on the estimates. This is because standardizing the gender gap in firms' pay policies involves adding and subtracting a constant to all observations. As a result, the distribution of this variable simply shifts to the left or to the right without changing its shape.

[30] According to the implications provided by Eq. (9), $\omega_j^m - \omega_j^f$ is determined by three main factors: a market-constant effect, α_k, denoting gender differences in employers' wage setting power, a taste-based discrimination parameter $\hat{\delta}_j$ and a residual term ρ_j.

[31] With this specification, not only characteristics effects, but also unexplained coefficient components of a traditional Oaxaca–Blinder gender wage gap decomposition (Oaxaca, 1973) are controlled for.

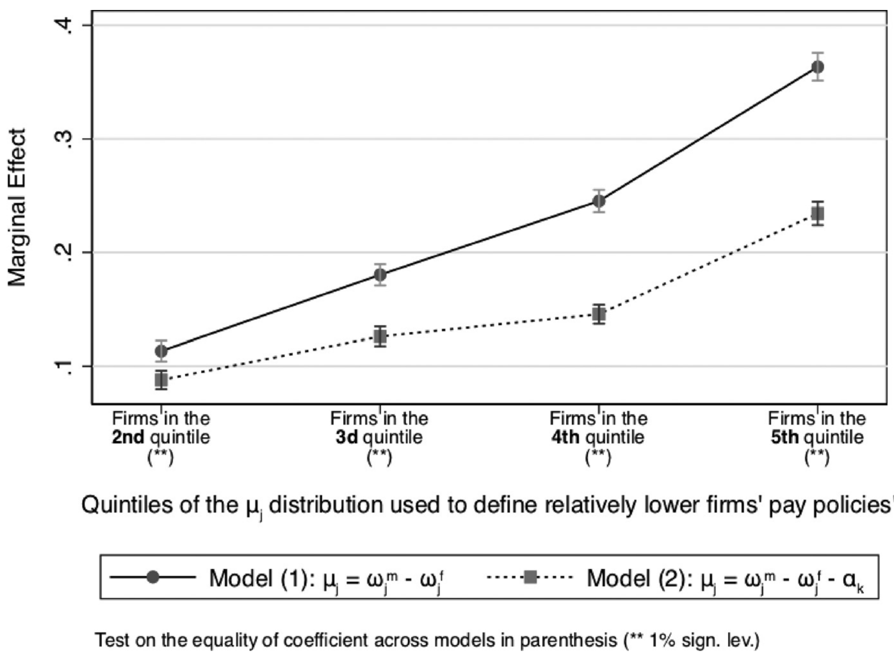

Fig. 3. Gender gap in firms' pay premiums and the gender wage gap.

policies. As discussed in Section 2.3, we assume that monopsonistic discrimination is embedded in market-constant effects α_k. However, interpreting the difference between b_θ estimated using the two alternative definitions of μ_j as the product of monopsonistic discrimination alone is difficult, given the strong homogeneity assumptions on which this interpretation rests.[32] Moreover, disentangling between monopsonistic mechanisms and other market-wide determinants of the gender wage gap, such as women comparative advantage in given sectors due to gender-specific skills, is not possible. Nevertheless, comparing these two estimates of b_θ still allows to derive a sound measure of the effect on the gender wage gap of factors, which are not specific of a given employer, but that are rather related to the labour and product market structure in which firms operate, while also conditioning on workforce composition.

Fig. 3 and Table 4 show the results of the model discussed above estimated on the sample of manufacturing sector workers selected along the lines discussed in Section 4. The graph in Fig. 3 shows how the coefficient b_θ varies when T_θ is defined using different quintiles of the distribution $F()$ and different metrics μ_j of the gender gap in firms' pay policies.

In general, the treatment effect is always strong and significant. When employed at firms with relatively lower female pay policies, women suffer an additional wage loss with respect to men of between 11% and almost 36%, depending on how the treatment variable is defined. These results imply that the gender wage gap conditional on observable characteristics, returns to such characteristics and individual time-constant heterogeneity grows substantially, with respect to its baseline level, in work environments that are less favourable for women. These results can also be interpreted as a test on the actual relevance of the ranking of employers provided by the gender wage gap in AKM firms' wage policies, while using the alternative identifying assumption of gender-constant firm fixed effects.

Differences in marginal effects across models (given by the vertical distance between each coefficient in the top panel of Fig. 3), are always significant and account for a reduction of around 30% in the conditional gender wage gap after taking into account the contribution of market-wide mechanisms. For example, when comparing the quintile of firms with least favourable female firms' pay policies to the most favourable quintile, the gender wage gap grows by an additional 36%, and by only around 23% if taking into account only workplace-specific factors that are independent of the labour- and product-market structure faced by firms. This implies that market-constant effects α_k explain around one third of the within-firms conditional gender gap. Thus, a substantial proportion of the variability of this gap seems to be employer-specific rather than market-specific, and it is more likely to be linked to factors such as taste-based discrimination or gender differences in compensating wage

Table 4
Gender gap in firms' pay premiums and the gender wage gap: summary of regression results

	Dependent variable: log daily wage	
Firm environment metric (μ_j)	Model (1) $\omega_j^m - \omega_j^f$	Model (2) $\omega_j^m - \omega_j^f - \alpha_k$
Coefficients		
$b_{\theta=0.2}$	0.113	0.088
P-value	(0.000)	(0.000)
$b_{\theta=0.4}$	0.180	0.126
P-value	(0.000)	(0.000)
$b_{\theta=0.6}$	0.245	0.146
P-value	(0.000)	(0.000)
$b_{\theta=0.8}$	0.363	0.234
P-value	(0.000)	(0.000)
F tests		
Age and tenure polyn.	225.9***	222.48***
Interactions with $1[g=f]$	1536***	1532***
Main occupation dummies	215.9***	215.1***
Interactions with $1[g=f]$	18.77***	18.79***
All covariates	1204***	1088***
Adjusted R^2	0.872	0.871
RMSE	0.128	0.128
N. firm effects	11,496	11,496
N. worker effects	401,624	401,624
N. of observations	1,435,613	1,435,613

*S.e. clustered at firm level. Significance levels: ***: 1%; **: 5%; *: 10%*
Results of the regression models presented in Eq. (10). The graph in Fig. 3 plots treatment effects and 95% CI for each parameter b_θ. The regressions include controls for human capital interacted by gender and a full set of firm, individual and year fixed effects.

[32] However, it should be noticed that geographical and industry proximity are often found to be good approximations of the heterogeneity in firms' labour market power by the recent literature, see in particular Azar et al. (2020a) and Azar et al. (2020b).

differentials.[33] In the next section, we provide a more direct and robust assessment of the relevance and size of these latter mechanisms.

5.3. Test for the presence of taste-based discrimination and compensating wage differentials

We now discuss the results obtained by estimating the model that was introduced in Section 3.2. In particular, we use the gender gap in firms' policies as the dependent variable of our regression model, and we test whether this difference can be predicted by proxy variables for taste-based discrimination and gender differences in compensating wage differentials. The regression equation reads as follows

$$\omega_j^m - \omega_j^f = \alpha_k + b_1\hat{\delta}_j^1 + b_2\hat{\delta}_j^2 + b_3\rho_j^1 + \hat{\delta}_j^r + \rho_j^r \quad (11)$$

where $\hat{\delta}_j^r + \rho_j^r$ is a composite residual, while α_k represent market-constant effects. We approximate α_k by three firm size dummies, two-digits (ISIC) sector fixed effects and thirty dummies for each of the local labour markets of the Veneto region, interacting all of these variables in some model specifications. We also include two dummy variables for firms above the median-level of average workforce age and above the median share of manual workers.

As discussed in Section 3.2, we have approximated taste-based discrimination using two proxy variables, which we denote $\hat{\delta}_j^1$ and $\hat{\delta}_j^2$, representing the presence of women at the top of the corporate hierarchy and the female share of workers, respectively.[34] The other explanatory variable of interest in the regression model is ρ_j^1, which we define as the part-time share within firms, measured as the ratio of full-time equivalent days worked part-time in a year over total days worked, and which captures the potential preference of women for workplaces providing flexible schedules.

In order to test more nuanced hypotheses on the mechanisms driving the gender gap in firms' pay policies, we have also performed an heterogeneity analysis by changing the dependent variable of the model. In particular, we have considered the gender gap in firm fixed effects interacted by occupation (manual or non-manual), as estimated through an AKM regression by gender. This variable represents sex differences in firm wage policies specific of blue-collar workers.[35] Thus, using this dependent variable we can test whether our proxy variables for taste-based discrimination and gender differences in compensating wage differentials have heterogeneous effects on blue collars, or whether they evenly affect the entire workforce.

There are two main mechanisms that could generate correlation between the residual term in Eq. (11) and the explanatory variables of interest. On one hand, these variables could be correlated with measurement error in the gap between male and female firms' wage policies. On the other hand, there could be simultaneity between the female share or the presence of female managers and the relative size of male and female firm wage policies. Given that we have estimated the AKM regression model excluding part-time workers, ρ_j^1 is less subject to these endogeneity problems, particularly for what concerns simultaneity, given that, in principle, a higher incidence of part-timers should not affect gender differences in full-time workers' pay policies, unless for the presence of spillovers related to compensating wage differentials.

In order to address the above mentioned identification threats, we propose two alternative identification strategies. First, we use lagged values of $\hat{\delta}_j^1$ and $\hat{\delta}_j^2$, computing these two variables over the period 1992–1995, which does not overlap with the years in which the AKM firms' pay policies are estimated. For this reason, the link between predetermined variables and measurement error is substantially weakened. Moreover, predetermined variables are independent of temporary supply- or demand-side fluctuations that could affect individual firm wage policies as well as the likelihood of having women at the top of the firms' hierarchy or a higher female share. At the same time, the predetermined proxy variables are still correlated with taste-based discrimination if this preference parameter is a persistent characteristic within companies.

An alternative estimation approach that we have implemented is two-stage least squares, where we have used the leave-out local-industry average of $\hat{\delta}_j^1$, $\hat{\delta}_j^2$ and ρ_j^1 as instruments for these explanatory variables of interest. If we assume discriminatory preferences to be relatively uniform across employers within narrowly defined labour markets, and schedule flexibility to be mainly an industry-specific characteristic, then the proposed instruments can be considered relevant, as they would be correlated respectively with taste-based discrimination and with amenities preferred by women. Regarding its validity, this IV approach can be a useful tool to address concerns related to the endogeneity determined by measurement error, since the proposed instrument is orthogonal to firm-level residuals potentially correlated with the proxy variables of interest. A drawback of this approach is its potential vulnerability with respect to correlation with supply and demand factors affecting the proxy variables at the industry and local level, while also influencing the gender wage gap in firms' pay policies.[36]

Table 5
Summary statistics on proxy variables for taste based discrimination and compensating wage differentials.

Variable	Mean	St. Dev.
Female manager	16.83%	
Lag female manager	15.02%	
Female share	0.465	0.204
Lag female share	0.433	0.245
Part-time share	0.072	0.096
Observations	**8859**	

All statistics are computed over firms. The number of observations refers to all firms observed during the period 1992–1995 that could be merged with the 1996–2001 sample.

Table 5 provides descriptive statistics for the independent variables of interest, computed on the sample of analysis. As can be noticed, around 7% of days worked within firms are part-time, the ratio of women is on average above 40% across workplaces, while more than 15% of companies are led by women. Moreover, there is an upward trend in female labour force participation and representation at the top of the corporate structure between the periods 1992–1995 and 1996–2001.

Table 6 summarizes the results of the regression models discussed above. In the left panel of the table firm fixed effects in the dependent variable are not interacted by occupation. In this case, it can be

[33] This finding seems coherent with the rather limited evidence available on this topic. In particular, Webber (2016) shows that monopsonistic discrimination is more driven by sorting of men and women across labour market structures, rather than by within-firms gender differences in the supply elasticity.

[34] We have computed the female share ($\hat{\delta}_j^2$) as the average proportion of female workers within firms across all years. Instead, given that explicit information on firms' ownership and management structures was not available, we have defined $\hat{\delta}_j^1$ as a dummy for the presence of women in non-manual occupations that were receiving the highest observed yearly earning within the firm, where the highest pay was defined with respect to all person-year observations. For firms with more than 60 person-year observations, we have relaxed this definition and considered as female managers also those women that were among the top 3% yearly income earners *and* one of the top 10 earners among all person-years observations in a given workplace.

[35] When the dependent variable is the gender gap firms' wage policies paid to manual workers, the sample size reduces. This is because only firms hiring both, male and female blue collars belonging to the largest connected set can be included in the analysis.

[36] Another limitation of the IV approach concerns the fact that leave-out shares must be computed at a more granular level than the fixed effects controlling for the market structure that are included in the regression model. Since we have computed leave-out shares at the two-digit sector and LLM level, fixed effects for LLM interacted by industry could not be included as controls in this regression.

Table 6
Regression results on taste-based discrimination and compensating wage differentials.

Dependent variable	*Gender gap in firms' premiums*			*Gender gap in blue collar firms' premiums*		
Model	OLS (1)	OLS (2)	IV	OLS (1)	OLS (2)	IV
Coefficients						
Female manager			−0.014			0.010
P-value			***0.572***			***0.683***
Lag female manager	−0.011**	−0.010*		−0.001	−0.001	
P-value	***0.035***	***0.078***		***0.836***	***0.808***	
Female share			−0.090*			−0.105**
P-value			***0.060***			***0.022***
Lag female share	−0.023**	−0.021*		−0.041***	−0.044***	
P-value	***0.011***	***0.052***		***0.000***	***0.001***	
Part-time share	0.092**	0.085*	0.092*	0.076**	0.119**	0.091*
P-value	***0.049***	***0.073***	***0.056***	***0.019***	***0.029***	***0.084***
F and χ^2 tests						
Avg. age, manual occ. share f.e.	2.09	1.20	5.60*	0.86	2.19	3.90
Firm size f.e.	10.44***		12.1**	14.93***		5.50*
Sector f.e.	2.49***		50.5***	50.1***		17.7
District f.e.	2.45***		117***	2.25***		109***
District×sector×firm size f.e.		1.08**				
All covariates	3.65***	2.68**	270***	2.31***	3.40***	162***
Kleibergen–Paap F stat.			162			161
Adjusted R^2	0.016	0.033	0.009	0.012	0.018	0.006
RMSE	0.180	0.179	0.180	0.190	0.189	0.189
N. of observations	8859	8859	8859	6896	6896	6896

S.e. clustered at 2-digit sector and municipality level. Significance levels: ∗∗∗: 1%; ∗∗: 5%; ∗: 10%.
The left panel of the table summarizes the results of regressions of proxies for taste-based discrimination and compensating wage differentials on the gender gap in firms' pay policies. The units of observation are individual firms. Basic controls include fixed effects for two classes of average age and manual worker share, three classes of firm size, two-digits sectors and local labour markets, which are then interacted in Model (2). Model (3) is estimated using leave-out local industry averages as instruments for female manager, female share, and part-time share. The right panel shows results obtained by changing the dependent variable, which is defined as the gender gap in firm wage policies paid to blue collar workers, as estimated by interacting firm f.e. with occupation in an AKM regression model by gender.

noticed that the presence of women at the top of the hierarchy is a significant predictor of the gender gap in employers' wage policies in the OLS model. In particular, this gap reduces by around 1 percentage point at workplaces lead by females, but the confidence interval is relatively large. When compared to a raw gap of around 20% among manufacturing-sector workers, this point estimate implies a reduction of about 5% in the gender wage gap. Similarly, a 10 percentage points increase in the female share of workers is associated to a reduction in differences between ω_j^m and ω_j^f of around 0.2 percentage points, which translates into a 1% reduction of the raw wage gap. However, the effect related to the presence of female managers is not robust when implementing two stages least squares in the third column, while the effect of the female share increases in size, but it is more noisily estimated with this approach.

When the dependent variable of the model is changed and only manual workers are considered (right panel of Table 6), results differ. Indeed, while the point estimates of the impact of being in workplaces with more women becomes more negative and more significant (implying up to more than a 0.4 percentage points reduction in the firms' gender gap for each 10 percentage points growth in the female share when using OLS, and a 1 percentage point reduction when using IV), the presence of female managers is instead not associated with a significant reduction in the gender wage gap in this case, irrespective of the estimation method. This difference in the results suggests that women at the top of the hierarchy may provide more favourable working conditions for female workers only in the case of clerical occupations. This finding is consistent with the results documented by Flabbi et al. (2019) in the Italian context, while using a different approach.

When studying the role of compensating wage differentials, Table 6 shows that, irrespective of the choice of dependent variable, firms with a relatively higher propensity of providing part-time contracts are able to pay women relatively less. This mechanism induces a growth in the conditional firm-specific gender gap of around 0.9 percentage point for each 10 percentage points increase in the share of days worked part-time at a given workplace. Moreover, this effect is stronger in some specifications and more significant among blue-collar workers. The presence of wage penalities for full-time women at firms where more flexibility is available is a novel evidence, given that most studies focus instead on penalties (or premiums) among part-timers (e.g. Devicienti et al., 2020; Elsayed et al., 2017). Hoever, this finding is coherent with studies on women's preferences for shorter schedules (e.g. Booth and van Ours, 2013; Del Boca, 2002), and with studies that suggest that part-time contracts are costly for firms, thus that they should be modeled as a non-wage amenity (Devicienti et al., 2018).

Overall, our results can be interpreted as evidence that taste-based discrimination and compensating wage differentials both play a significant role in driving the gender gap in firms' compensation policies within workplaces. This evidence seems coherent with the most recent studies adopting a similar approach. In particular, Bruns (2019) shows that firms opting out from centralized collective agreements, which arguably exert more wage setting behaviour and which are able to better exploit incentives provided by their preferences toward women or by female workers' hedonic considerations, tend to show larger gender gaps in compensation policies in Germany. Partly due to the limited precision in measuring employers' preferences toward women, our results suggest that taste-based discrimination has only a quantitatively small impact on the overall gender wage gap. However, this result could also be a consequence of the downward-rigid wage structure characterizing Italy, an institutional factor that tends to reduce the amount of employers' pay setting power (Devicienti et al., 2019) and that is likely to drive our results closer zero compared to the outcomes that would be observed in a decentralized wage setting equilibrium.

6. Conclusions

In this paper, we have shown that a simple static model of taste-based discrimination in monopsonistic labour markets provides a coherent framework to interpret the gender gap in firms' wage policies. This component of the earning differential between men and women is estimated through an AKM regression model (Abowd et al., 1999), and its importance has been documented, in different contexts, by several recent empirical studies (e.g. Bruns, 2019; Card et al., 2016; Casarico and Lattanzio, 2019; Coudin et al., 2018; Morchio and Moser, 2019; Sin et al., 2020).

We have provided a theoretical discussion of the conditions under which this residual component of the gender wage gap can be attributed to elements such as taste-based and monopsonistic discrimination, or compensating wage differentials. Moreover, we have presented an empirical application, introducing methods to test for the presence of such mechanisms while controlling for a large set of confounding factors.

Using matched employer-employee data on Italy, we have shown that women working in the manufacturing sector suffer wage losses of up to 36%, with respect to men, due to factors that are independent of their characteristics and abilities, as they are instead related to firm-specific mechanisms. Moreover, about one-third of this gap is market-specific, thus it is related to the labour- and product-market structure faced by firms. By documenting a positive relationship between the gender gap in firms' pay policies and traditional proxies associated to discriminatory preferences, namely, the presence of women at the top of the firms' hierarchy and the female share of workers within firms, we have provided robust evidence on the presence of taste-based discrimination. However, partly due to the quality of these proxy variables, both of these effects were small in magnitude. Moreover, for what concerns the presence of female managers within firms, its effect on the gender gap was found not significant among women in manual occupations.

We have used the same approach to test for the presence of compensating wage differentials, using the share of part-time work to approximate for non-wage amenities potentially preferred by women. We have shown that women tend to prefer work environments where more part-time contracts are available, as they are earning less in such places. Moreover, this negative effect on female wages is significant despite the fact that we consider only full-time employees, and seems to be stronger among workers at the bottom of the firm's hierarchy.

Our empirical findings are coherent with the implications of the static model presented in this paper, suggesting that this simple interpretative framework represents a useful tool for future research. Further promising applications of our method concern the design of tests on the implications of Becker's theory, among which the relationship between taste-based discrimination and the product market structure (e.g. Heyman et al., 2013) or firms' survival rates (e.g. Weber and Zulehner, 2014), in particular in context where more precise measures of employer-specific discrimination are available. Similarly, impact evaluations on policies such as the introduction of gender quota in managerial boards (e.g. Bertrand et al., 2019; Maida and Weber, 2020; Matsa and Miller, 2013) can also derive useful insights by the regression approaches discussed in this paper.

More generally, given that the interpretative framework provided by this paper can be used to construct consistent tests on several firm-level mechanisms driving the gender pay gap, future research on affirmative action policies could derive useful results from this approach, improving our understanding of the most important drivers of discriminatory differences in wages in several contexts.

Appendix A. AKM regression results

In this Appendix, we provide details on the AKM regression estimation. Before showing the AKM regression results, we provide some evidence on whether the assumptions of this model can be considered reasonable in our sample. Following Card et al. (2016), we test whether (gender-specific) co-workers' wages have a good predicting power for the pay of workers who change their job. Fig. A.1 computes the average wage of employees who work at two different firms for two consecutive years, where such average is computed by quartiles of co-worker wages at origin and destination firms.[37] As can be noticed, employees who move upward, form low-paying firms to high paying ones, face wage gains that are relatively symmetric to wage losses faced by workers who move in the opposite direction. Similarly, job movers who stay in the same quartile have a relatively flat wage dynamic.

The evidence provided by Fig. A.1 suggests that match effects, such as job-specific productivity shocks, have a limited impact on wages. Indeed, firm-specific factors influence individual earnings of both genders in a fairly similar way between job stayers and job movers. A second evidence supporting the AKM assumptions is the relatively parallel trend followed by job movers at origin and destination firms. The only discrepancy is the relatively flatter trend of workers in the fourth quartile of origin who move to a firm in the same quartile, with respect to the more pronounced seniority profile observed for other workers in the fourth quartile of origin who move downward. However, this tendency is present among both men and women and it is quite small in magnitude.

Table A.1 summarizes the results of the AKM model, separately form men and women, on the sample of gender-balanced manufacturing firms belonging to one of Veneto's local labour markets. It can be noticed that overall wage dispersion is higher among men. In both cases, the largest contribution to total wage variance is given by the joint effect of individual time-varying and time invariant characteristics and by the returns to such endowments. Moreover, the regression residual is larger among women, implying that the model fits better the data in the case of men.[38] The relatively worst fit of the model in the female sample is also reflected by the negative sorting term observed among women, as this component tends to be biased downward the higher the measurement error (see, among others, by Andrews et al., 2008).

In the context of the present analysis, the most interesting element of earnings variability is represented by the variance of firms' pay policies. Firm wage premiums provide a larger contribution to wage dispersion for women (19%) than for men (10%). In general, this result is consistent with our theoretical model, given that taste-based discrimination represents an element of variability in firm wage policies that is absent in the case of men. Also a more negative correlation between firm wage policies and human capital, at least in principle, could be considered consistent with our theoretical model, given that firm's wage policies paid to women should be considered distorted by taste-based discrimination. However, it can't be neglected the possibility that this result could be mostly driven by a larger measurement error in women's firm-specific wage residuals.

To investigate this issue, we have compared the fit of the model of the AKM regression with an alternative specification, in which each worker-firm pair effect is estimated by a separate dummy variable. This alternative specification captures any role played by job-match effects, which could be relevant if, due to factors associated to matching quality or to differences in wage posting behaviour along unobserved dimensions, firms were providing workers with highly heterogeneous compensation policies. Results presented in the lower part of Table A.1 suggest that the performance of the linearly additive AKM model is quite similar to

[37] The figure shows transitions from the first and fourth quartiles only. Similar patterns are observed also for quartiles at the middle of the co-workers' wage distribution.

[38] As shown by Kline et al. (2020) using the same database employed in our analysis, the actual variance of firm- and individual-fixed effects estimated through the AKM model is upward biased, while their covariance is downward biased. Given that the main results of the paper rely only on first moments of these parameters, we do not compute bias-corrected measures of this variance decomposition.

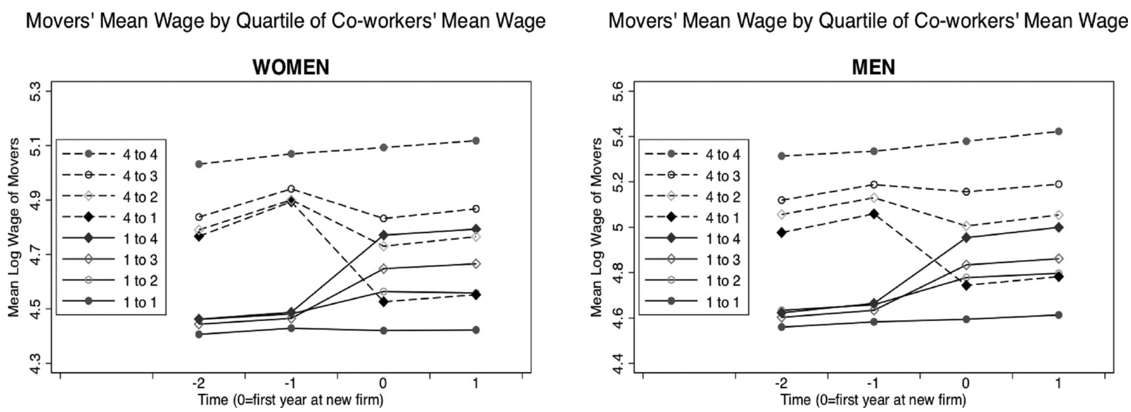

Fig. A.1. Mean wages of job changers at manufacturing firms, classified by quartile of Co-worker average wages at origin and destination firm. The figure shows the mean wage of workers who change job and work at least two years with two different employers during the period 1996–2001. Jobs are classified by quartile of gender-specific co-worker wages in the last year at the old job (origin firm) and in the firs year at the new job (destination firm).

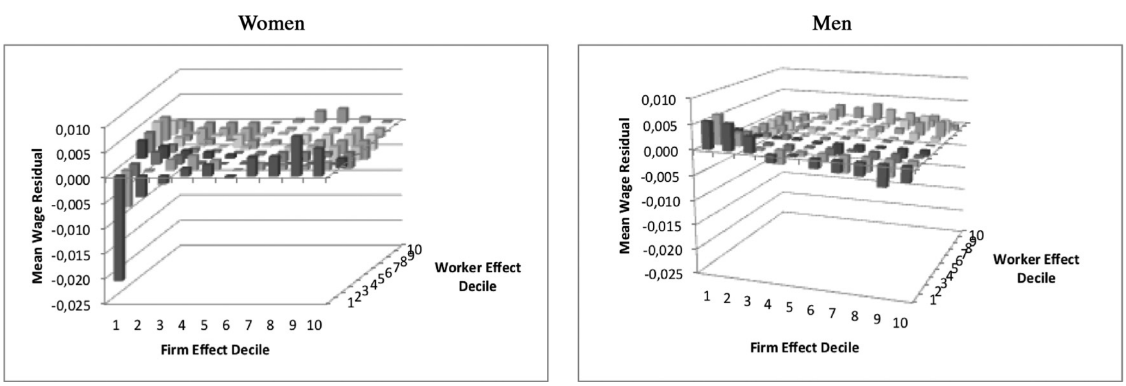

Fig. A.2. Mean AKM residual by decile of worker and firm effects. The figure shows the mean wage residual derived from the AKM regression model. The residual is computed separately by gender on 100 bins, classified by decile of estimated gender-specific person and firm effects. The sample is composed of 8859 gender-balanced manufacturing firms considered for the analysis of the gender wage gap.

Table A.1
AKM results among gender-balanced manufacturing firms.

	Women		Men	
$\mathrm{var}(\omega_j)$	0.015	19%	0.014	10%
$\mathrm{var}(x_{it}\beta + \eta_i)$	0.049	63%	0.111	79%
$2 * \mathrm{cov}(\omega_j, x_{it}\beta + \eta_i)$	−0.005	−7%	0.007	5%
$\mathrm{var}(e_{it})$	0.020	25%	0.008	6%
$\mathrm{var}(w_{it})$	0.079	100%	0.141	100%
RMSE of AKM model	0.168		0.107	
RMSE of match model	0.161		0.089	
Variance of match effects	0.002		0.003	
N. Observations	607,759		853,125	

The table presents the wage variance decomposition based on the AKM regression model. The parameters of the regression are estimated separately by gender on the entire database of Veneto's private sector. Results of the table are instead computed considering only the sample of gender-balanced manufacturing firms selected along the lines discussed in Section 4. The variance of match effects is estimated as the difference in mean squared errors of the AKM model and of a regression with separate fixed effects for each worker-firm pair, adjusting for differences in degrees of freedom between the two models.

the one of the job-match model. Indeed, the implied variance of match effects explains at most 2.5% of the total wage variance for both, men and women. Thus, we can conclude that the relatively larger residual observed among women is not linked to an incorrect specification of the linearly additive model, but rather to idiosyncratic shocks that are not related to job match effects.

To further test the role of the regression error, and its potential impact on the estimated parameters of the AKM model, following Card et al. (2013) we have computed the average AKM error term for 100 bins of firms and workers, classified according to deciles of firm effects and worker effects. Fig. A.2 shows the result of this test, separately by gender.[39] Wage residuals within each bin do not tend to zero by construction (Card et al., 2013), but should be reasonably small in absolute value by assumption. Indeed, systematically large positive (negative) errors for given groups of low- or high-wage workers and firms can be interpreted as an indirect evidence of omitted factors that could bias the estimates of the AKM parameters. Fig. A.2 shows that, even if there are some larger deviations among low-paid male and female employees in the first decile of workers' effects, all of the averages are quite small in absolute value, as they are uniformly below 2%.

[39] In order to provide the most tailored picture of the distribution of the AKM residual, Fig. A.2 is computed considering Veneto's gender-balanced manufacturing firms that were not only active in 1996–2001, but also observed at least once between 1992 and 1995. Indeed, when testing for the presence of taste-based discrimination, we have used lagged proxy variables measured during the period 1992–1995, further restricting the sample.

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