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Abstract

In this paper we use a random-coefficient approach to estimate frontier earnings functions by gender, marital status and north-south location for Italy. The results are used to generate estimates of wage discrimination. Although the overall discrimination measure is ambiguous we find that this is due to the counter veiling effect of education and tenure. Most southern-married women with high school or university education are to be found in the public administration sector where they are relatively better paid. The results show that it is education that removes discrimination, rather than sector of activity. Our results also support the crowding-in hypothesis. Southern-married males earn less if they work in sectors in which there is heavier concentration of females.

I Introduction

The issue of wage discrimination, defined as the unequal treatment of equally productive individuals, is a matter of concern for policy makers in all developed countries. Several explanations for wage discrimination have been advanced. Female workers are as productive as their male counter-parts, but they are paid a lower wage by employers who either have a "taste" for discrimination (Becker (1957), or have incomplete information about their productivity (Aigner and Cain (1977)). They may also be crowded in low-paying occupations (Doeringer and Piore (1971), and Bergmann (1974)).

A study by the European Commission[1] shows that the average (net) earnings differential for manual workers in the European manufacturing sector was 28 percent in 1991. Italy was not in the study because data were not available. Nevertheless women in the Italian labour market are considered to be at a disadvantage with respect to men and there is some evidence to support this. The available data shows that female earnings were about 76 percent of male earnings in 1987 (de Luca and Bruni (1993)).[2]

During the eighties the Italian government put much effort into improving the condition of female[3] employees in the labour market. Any resulting

[1] European Commission, Directorate General for Employment, Industrial Relations, and Social Affairs, (Ch.6, 1994).

[2] de Luca and Bruni (1993) note the absence of data specifically collected to study earnings statistics by gender.

[3] In this period the male labour force grew by O .37 percent only, but male employment was reduced by 2.5 percent. The female labour force increased by 15 percent and female employment went up by 9.3 percent.

improvements can be attributed to two factors. First, nearly all the new jobs were created in the service sector, traditionally more suitable to women. Second the eighties saw the development of an Equal Opportunity Policy with the formation of equal rights commissions both nationally and at the local level; the spreading of back-to-work courses (mostly in the north); and the diffusion of affirmative action in some public and private companies.[4]

Given the concern about female labour market conditions, and the size of the Italian economy, it is important to have relevant empirical studies. Despite the importance of the issue there is, to our knowledge, only one study of wage discrimination in Italy. Lucifora and Reilly (1990) estimate discrimination among unionized workers in the industrial sector with no allowance for regional or marital status differences. Their estimated discrimination coefficient is 16.8 percent.

Most empirical studies of wage discrimination follow the "index number" approach first suggested by Oaxaca (1973).[5] More recently work using the stochastic frontier approach have appeared. Boehm and Hofler (1987) first employed the frontier approach to measuring racial discrimination in the US housing market. Robinson and Wunnava (1989) adopt this approach to estimate discrimination against women. Using data on females only from the US Current Population Survey (CPS) for 1983 they estimate an earnings frontier and interpret the degree to which females lie below this frontier as due to discrimination (less any labor market inefficiency). Hunt-McCool and Warren, Jr. (1993) use data from the Panel Study on

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[4] For more details see for example Liviraghi (1989).

[5] Discrimination is measured as that part of the wage gap that cannot be explained by differences in the individual productivity.

Income Dynamics to estimate an earnings frontier.[6] They write: "Since actual earnings cannot, by definition, exceed potential earnings, the disturbances are nonpositive,..." (Hunt-McCool and Warren, Jr. (p. 199, 1993)). They interpret the gap to the frontier as a measure of the extent of inefficiency. Finally, Slottje et al (1994) use a stochastic frontier model and data on US baseball players' performance to estimate discrimination by race.

Given data of the type used by Slottje et al (1994), a homogeneous group for which data on performance - at the individual level - is available, the stochastic frontier should generate a meaningful estimate of the earnings frontier. The residual will be easy to explain and use to compare and contrasts various subgroups that are of interest. Such data is rare however. Most studies use household survey type data and interpretation of exactly what is captured in the one-sided term is not so straightforward. This is obvious from the different interpretations of their respective results by Robinson and Wunnava (1989) and Hunt-McCool and Warren, Jr. (1993).

A further problem arises in that it cannot be guaranteed that the observations will all lie below or above the frontier. While most authors estimate earnings frontiers, Hofler and Murphy (1994), also using the

[6] Their sample covers male household heads who were employed in 1979 and reemployed in 1981, but were unemployed in 1981.

CPS data for 1983, estimate a reservation wage frontier.[7] We return to this issue in section 2.

A paper which addressed this inconsistency between earnings and reservation wage frontiers is Polachek and Yoon (1987) who estimate a two-tiered earnings frontier using the Panel Study on Income Dynamics for 1981. Their error structure consists of three parts: a symmetric one; a nonpositive one-sided error term; and a nonnegative one-sided error term. They generate estimates of both employer and employee ignorance.

In this paper we use a representative household survey data set for Italy (covering 1989) to estimate wage equations and discrimination on the basis of gender, marital status and location. We generate an earnings frontier by estimating a random-coefficient model, as developed by Hildreth and Houck (1968), which has also been used to estimate frontier production functions (see Kalirajan and Obwona (1994)). This methodology has not previously been applied to earnings functions.

Unlike the stochastic frontier there is no question of generating a reservation wage frontier. Further, it allows for varying parameters on the constant term and on the human capital variables. This is important if we consider that ability, quality of education and tenure may differ from person to person. The random-coefficient method is useful in modelling such heterogeneity among employees.

[7] The earnings frontier is written as: $y = X\beta + v - u$ where u is the nonnegative one-sided component that measures the shortfall from potential earnings. The reservation wage frontier is written as: $y = X\beta + v + u$ were u is the nonnegative component that measures how far actual wages exceed the person's reservation wage. To clarify, Hunt-McCool and Warren, Jr. (1993) write that the disturbances are nonpositive which means that they write the earnings frontier that they estimate as $y = X\beta + v + u$.

The paper is organized as follows. In section 2 we present the methodology. The data is discussed in section 3 while section 4 gives the results of the wage equation estimates as well as a discussion of the estimated discrimination. Section 5 concludes the paper.

II The Model and the Estimation

There are several drawbacks to using the stochastic frontier to estimate frontier earnings functions. It would appear to be particularly troubling that this approach can generate an earnings frontier or a reservation wage frontier. What type of stochastic frontier can be estimated is data driven[8] which makes this method inappropriate. The random-coefficient approach described below has the advantage of only generating an earnings frontier. Furthermore the stochastic frontier is not useful if the slope coefficients vary, as it is a neutral shift of the conventional earnings function.[9] This may happen if even for the same levels of human-capital different levels of earnings are observed, due to employer/employee ignorance, measurement error, and quality differences in the human capital asset.[10] To model this possibility a random term is added to the parameter vector of the earnings function, which we assume is of the semi-logarithmic type:

[8] We estimated stochastic frontiers for our data set and in several cases this was not possible, but it was possible to estimate the reservation wage frontier.

[9] We note that from the point of view of measuring discrimination the two-tiered earnings frontier would not add more than the stochastic frontier. Moreover, it is always going to be difficult to estimate, particularly so for samples of small size. Moreover the measures of ignorance will be influenced by the distributional assumptions. Polachek and Yoon (1987) mention that the robustness of the three-component model remains to be assessed. Evidence from the frontier production function literature would suggest that distributional assumptions will affect the findings, potentially quite severely.

[10] Swamy and Tavlas (1995) write that parameter randomness may also be due to nonlinearities not captured by the particular specification adopted, as well as omitted variables.

$$ln\,(y_i) = \sum_k (\beta_k + v_{ik})\,(x_{ik}) \qquad i = 1, \ ...n \qquad (1)$$

where: y is the net hourly earnings of each person; the x are human-capital variables, and intercept; v is a vector of random disturbances; and the subscripts i and k denote the ith employee and kth employee characteristic respectively. Each employee's parameter vector β_{ik} is allowed to vary from the mean response vector $\bar{b}$ by some v_i. There is a particular response coefficient for each variable and each observation. With regard to the v_{ik} we assume that: $Ev_{ik} = 0$; $Ev_{ik}^2 = \alpha_k$; and $Ev_{ik}v_{im} = 0$ for $i \neq j$ and for $k \neq m$. Letting $\Sigma\, x_{ik}v_{ik} = u_i$ we can write (1) as:

$$y = X\beta + u \qquad (2)$$

where X is a NxK matrix of the independent variables, and y, β and u are vectors of order N, K and N respectively. An unbiased estimator for α is given by:

$$\hat{a} = (G'G)^{-1}G'\dot{r} \qquad (3)$$

where G = $\dot{M}\dot{X}$; M = $(I - X(X'X)^{-1}X)$; $r = y - X\beta$; and a dot denotes a matrix (vector) derived by squaring each element. The estimate of the mean response vector $\bar{b}$ is given by:

$$\hat{\bar{b}} = (X'\Theta^{-1}X)^{-1}X'\Theta^{-1}y \qquad (4)$$

where Θ is the covariance matrix of the u's:

$$\Theta = \begin{pmatrix} x'_1 a x_1 + s^2 I & 0 & \cdots & 0 \\ 0 & x'_2 a x_2 + a^2 I & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & \cdots & x'_N a x_N + s^2 I \end{pmatrix}$$

Once the estimates of α and σ^2 are inserted equation (4) gives the feasible GLS estimator. We are also interested in calculating the individual response coefficients. BLU estimates are given by (see Griffiths (1972)):

$$\hat{b}_i = \hat{\bar{b}} + f x'_i [x_i f x'_i]^{-1} (y_i - x_i \hat{\bar{b}}) \qquad (5)$$

where $f = \mathrm{diag}(\hat{a}_1, \cdots, \hat{a}_K)$

There is no a priori reason for assuming that the coefficients on variables that are not individual specific, like the sector of activity and the unemployment rate, vary. Hence, we assume that these coefficients are fixed and we impose the restriction that the estimates of α for these coefficients are zero. This restriction is imposed when solving for $\hat{\bar{b}}$ and $\hat{\Theta}$. Finally, to test the validity of the random coefficient model we use a modified form of the test proposed by Swamy (1970):

$$\sum_i \frac{(\hat{b}_i - \hat{b}_{GLS})' X'_i X_i (\hat{b}_i - \hat{b}_{GLS})}{\hat{s}_i^2} \qquad (6)$$

Where the β_i are the random coefficient estimates and the β_{GLS} are the feasible GLS estimates without random coefficients, and the test is distributed as a x^2 with degrees of freedom equal to the number of restrictions.

Our interest in this study lies in estimating the wage gap attributable to a move from one wage structure (female) to another (male). In our judgement it is not true that the distance to the frontier, of say single-female employees, measures discrimination, as Robinson and Wunnava (1989) claim. Rather it is attributable to several factors such as measurement error, differences in quality of education and employer/employee ignorance, and possibly discrimination. We propose to measure the discrimination between two groups (eg female-male) as the difference in the two frontiers that result when applying the two respective maximum response coefficients (i.e. the largest coefficient estimated for each variable). To implement this, we first calculate the potential wage (i.e. the maximum possible given a person's characteristics) for each individual of each female group:

$$\ln(\hat{y}_i^*) = \hat{b}_0^* + \sum_k \hat{b}_k^* x_{ik} \qquad (7)$$

where a star denotes the maximum estimated response coefficient within the respective female group, as well as the potential wage. The frontier is given as:

$$GAP_i = \frac{e^{y_i}}{e^{\hat{y}_i^*}} \qquad (8)$$

This is the gap between actual and potential wage, in percentage terms.

Using the b^* for two different samples (female-male) on one reference group (female) we generate two estimates of the potential wage and two frontiers. One frontier corresponding to females facing the female wage structure and the other corresponding to females facing the male wage structure.[11] The difference between the two GAP indices thus obtained gives us a measure of the discrimination that each female faces. The interpretation of this difference is that if the GAP index for (for example) single-female-south characteristics calculated using their maximum response coefficients lies above (is larger) the GAP index for single-female-south characteristics using the maximum response coefficient from the single-male-south group, then females are doing better than males. This is so because a higher frontier implies higher potential wages and hence a more favourable wage structure (for females in this case). The resulting discrimination coefficient will be positive in this case of reverse discrimination. Vice versa, a negative coefficient indicates that women are discriminated against. The discrimination coefficient, being the difference in the two GAP indices, is a percentage measure of how much higher (or lower) female potential wages would have been had they faced the male wage structure.

[11] We follow the usual convention of assuming that males are the non-discriminated group.

III The Data

In this study we use the 1989 wave of the Bank of Italy "Survey on Consumption by Italian Families" (SCIF). The selected sample includes 6136 individuals, both household heads and single persons living with their family and working as employees. We control for marital status when estimating the earnings frontiers as the underlying demographic structure of single and married individuals is very different. The dataset is a family survey and hence the average age of married individuals (the parents) is substantially higher than that of singles (the children).[12]

We created the following subsets of the data (number of observations given in brackets as well as the abbreviation used): South:[13] Female-Single (143, SFS); Female-Married (405, MFS); Male-Single (219, SMS); Male-Married (1247, MMS). North: Female-Single (560, SFN); Female-Married (962, MFN); Male-Single (794, SMN); Male-Married (1806, MMN). There are important differences between the northern and the southern samples. Participation rates for women and men have always been lower in the South. During the course of the eighties the gap between the Northern and the Southern regions widened. The gap between southern and northern unemployment rates increased, partly because south-north migration declined substantially. In 1989 male unemployment was 4 percent in the North and 15 percent in the South. Another important difference between the two regions is the structure of employment. A

[12] No single individuals have children. Individuals who are either divorced or widowers have been excluded from the sample as for most of them there is no information about the number of children.
[13] The north-centre (which we refer to simply as the north) includes the following regions: Piemonte; Valle d'Aosta; Lombardia, Trentino-A lot Adige; Veneto; Friuli-Venezia Giulia; Liguria; Emilia-Romagana; Toscana; Umbria; Marche, and; Lazio. The south includes: Abruzzi; Molise; Ca npania; Puglia; Basilicata; Calabria; Sicilia, and; Sardegna.

higher percentage of workers in the south is employed in agriculture and the service sector (the latter almost completely represented by Public Administration).[14]

The dependent variable (HW) used is net hourly earnings as there is no information about gross hourly earnings. The use of net wages may lead to understate the gender wage gap as men usually work longer hours, and therefore may have higher annual earnings and pay higher taxes. However, looking at the distributions of hours of work for men and women in our sample we find very similar distributions for single men and women. As for married workers, 87 percent of married women work full-time and all the year around. The lower average weekly hours are mostly due to the fact that more women than men have public sector, 36 hours-per-week jobs. Married women also cannot deduct family expenses (such as Medicare, children's education, some insurance policies) from their tax-bills.

We focus on two specifications: a) A hedonic form, and; b) a reduced form. We include only human-capital variables, education and tenure, in the hedonic form. Years of schooling may reflect discrimination as women invest less in education in anticipation of future discrimination in the labour market. There is no evidence for Italy of such under-investment. Women are, on average, better educated than men.[15] We include three dummies, to allow for non-linear effects of education on the wage rate:

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[14] Meschi (1994) tests for north-south parameter constancy using a heteroscedastic consistent Wald test proposed by Honda (1982). The null hypothesis of parameter constancy is rejected in all cases.

[15] For our sample we have that single females spend an average of 11.54 years at school while men spend an average of 10.75 years at school. For married women and men the numbers are 11.28 and 9.75, respectively.

EDUCl=1 if Junior-High school was completed, O otherwise; EDUC2=1 if (the equivalent of) A-levels (high-school leaving exams) were taken, O otherwise; EDUC3=1 if a university degree was obtained, O otherwise. The reference group are individuals with elementary or no education.

Finally we include tenure (TENURE) in the current job/sector of activity as a proxy for work experience. The choice of the tenure variable rather than work experience was dictated by the possible measurement errors in the all-life work experience of married women. However, current job tenure may have a different effect on the wage than experience before the current job. We have therefore added, in turn, past experience and total work experience to the wage equations. They have always turned out insignificant. Measurement error and endogeneity are likely to be problems with this kind of variable. The issue of endogeneity has been addressed by Blinder (1973), Mincer and Polachek (1974) and Zabalza and Arrufat (1985). If women work less because they are paid a lower wage, then experience is endogenous and the estimated wage equation will be biased. We allow for endogeneity by using the predicted value of tenure in the estimations.[16]

In the reduced form equation we include the human-capital variables as well as dummies for occupation, sector of activity and several other factors, as omitting relevant variables may cause bias in the estimates. These additional explanatory variables are: WORKFT = dummy, 1 if individual works part time or part of the year, 0 otherwise; REGUNEMP = the regional unemployment rate;[17] CIGRATE = the regional ratio of

[16] Preditive equations available from the authors, upon request.

[17] In the south the regional unemployment rate varies from 18.40 to 41.40 for females and from 7.76 to 19.21 for males. In the north the rate's range is 6.90 to 20.10 for females and 2.47 to 8.39 for males.

redundancy hours in Industry to total hours worked in industry.[18] This variable is included to capture hidden unemployement.[19] QUAL1 = dummy, 1 for manual worker, 0 otherwise; QUAL2 = dummy, 1 for clerks and school teacher, 0 otherwise. The reference group for occupation are employees who are managers. Further we included sectoral dummies: SETT2 = dummy, 1 for construction industry, 0 otherwise; SETT3 = dummy, 1 for the industrial sector, 0 otherwise; SETT4 = dummy, 1 for retailing, catering and hotelling, 0 otherwise; SETT5 = dummy, 1 for transport and communication, 0 otherwise; SETT6 = dummy, 1 for banking and insurance, 0 otherwise; SETT7 dummy, 1 for services to companies and enterprises, 0 otherwise; SETT8 = dummy, 1 for public administration, 0 otherwise; SETT9 = dummy, 1 for other services, 0 otherwise. The reference group for sectoral activity are employees working as agricultural labour. Finally we include DEN = the proportion of female workers by occupation, sector and region. The density variable is included to allow for a test of the crowding-in hypothesis.

We assume that the occupation and sector of activity dummies are exogenous variables. However, this may not be so if access to some jobs is restricted to men either because of discrimination or because women choose not to enter these occupations. In order to correct for this kind of sample selection bias it is necessary to incorporate a model of occupational choice (see Reilly (1989)). Unfortunately the information needed is unavailable in our dataset.[20]

[18] In the south this ratio varies between 0.79 to 9.71. In the north the range is 1.45 to 5.06.
[19] REGUNEMP and CIGRATE are obtained from ISTAT (1990).

IV Results

The random coefficient estimates are given in tables 2 through 9.[21] Tables 2 through 5 give the mean response coefficients for the hedonic and the reduced form estimates. Tables 6 through 9 give the range of the coefficient estimates for the two forms and the eight different samples.[22] The results for the hedonic model appear quite reasonable. Higher levels of education always yield higher returns. Except for EDUC1 for single females (north and south) the variables are always significant at least at the 5 percent level.[23] Tenure and its square are always (jointly) significant, at least at the 10 percent level, except for married females in the north. The effect of tenure is non-linear, the wage increasing at a decreasing rate with additional years of experience. The results show a flatter earnings profile for marrieds.

The results for the reduced form equation are less strong. Particularly for the smaller sample sizes we expect problems with multicollinearity. Nevertheless the x^2 statistics indicate that we can reject the hypothesis of fixed coefficients for the human-capital variables in all cases at the 1 percent level. The reduced form would appear to fit better for males, particularly in terms of the education variables. A possible reason is that education for females is more strongly correlated to sector of activity than

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[20] Variables that are highly correlated with occupational choice but uncorrelated with the wage are needed. Family background variables have been used in the literature.
[21] The wage equations were estimated in semi-logarithmic form and we note that a continuous variable measures the proportional change in the wage rate due to a unit increase in this variable. The coefficient of any dummy variable measures the differential effect of being in the included group relative to the reference group and has to be calculated as exp(, 1 when the dependent variable is in logs.
[22] The t-ratios are calculated using the White (1980) heteroscedastic-consistent covariance matrix. The correction for using a predicted variable is also made.

for males. The reduced form results are also stronger for the northern samples. We note that the inclusion of occupational dummies leads to lower coefficients on education, as is usually the case. This is due to the fact that access to certain occupations (eg. teacher) requires certain levels of education.

The dummy for part-time, WORKFT is only significant in three cases and large and positive in two of those. This is in line with expectations as part-time employees earn the same gross wage as individuals who work fulltime (they have to be paid 50 percent of the yearly full-time wage) but pay less in taxes. The variable capturing unemployment, REGUNEMP, is significant for northern-married males with the expected negative coefficient in that case. It perhaps reflects the impact of higher unemployement on the reservation wage of norther married males. CIGRATE is only significant for marrieds in the south but with a positive, though quite small, coefficient.

QUAL1 and QUAL2 are always negative, as expected. QUAL1 is always significant for males and for the northern samples. From tables 4 and 5 we see that SETT8 (public administration) has the strongest impact on earnings for single southern females and a strong impact for married southern females. Southern married women in SETT8 have a 41 percent higher wage than the reference group. This is particularly significant as a substantial proportion of females are located in this sector (47 percent for married southern females). The occupational effects for married southern (and northern) males are quite even across sectors. The variable DEN is

[23] We set a on EDUC1 for single females (north and south) equal to zero and hence the coefficient is fixed. The rationale is that since it is insignificant it is not reasonable to expect a precise estimate of the range. We maintained this restriction when estimating the reduced from equations.

significant and negative for southern-married males, which supports the crowding-in hypothesis.

In all cases there is a large range on the coefficients. This suggests that education and tenure vary in terms of their impact on a person's earnings potential. Since the variables are proxies we expect that some of the variation is due to quality differences, i.e. different values are attached to the same kind of degree or the same length of tenure. The constant term captures unobserved effects. The range is narrowed in the reduced form model, as we would expect. The remaining, within group, variation is due in part to differences in ability, at least as perceived by the employer.

IV.1 The Wage Discrimination Estimates

The results for the gender specific wage discrimination are given in table 10. The top half gives results for the hedonic form, while the bottom half gives the reduced form results. We report an overall (or aggregate) discrimination figure, as well as the disaggregated statistics for the constant term, education and tenure.[24] While the measure of the shortfall from the potential wage is sensitive to extreme values we note that this is not true for our measure of discrimination between two groups, as the extreme values cancel out.

To reach an unambiguous conclusion the two indices should not cross and the resulting overall measure will have an entirely positive or negative range. This is only true for southern married women in the hedonic case.

[24] For example, for the effect of education we use only the male ß* on education (all other ß*'s are the estimates for the female group) when calculating the differences between the two frontiers.

For the reduced form this is true only for southern single women. In nearly all cases we find that the result is less strong when we go from the hedonic to the reduced form.

For the single groups the apparent outcome is that males are discriminated against. This may be because men are more likely to enter the private sectors like construction, and face lower starting wages than women employed in the public sector. Married females are the only case where there is evidence of discrimination. The neutral shift, due to the constant term, is negative, i.e. indicates that females earn less than men, everything else being equal.[25] However, tenure reduces discrimination against females, while education reduces discrimination in the south, while it has the opposite effect in the north.

[25] We assume that there should not be a real difference in ablility between the best male and female.

IV.1.1 Southern Married Females

Of particular interest are the results for southern married females. In table 11 we report the mean discrimination coefficient for various groups. In all cases the reported group means are statistically different from the means of the reference groups and furthermore the sign switches in all cases. Here we note that females with only junior high school education are discriminated against, while this is not true for women with A-levels or higher education. Also, women with manual worker qualifications are discriminated against while women with clerical and teaching qualifications are not. In terms of the sector of activity we not ehtat women working in the industrial sector and in retailing, catering and hotelling are discriminated against, while women working in public administration are not. Indeed, if we take all females outside of public administration we find a significant and negative mean discrimination coefficient.

Women with junior high school education are evenly distributed across the different occupations, QUAL1 and QUAL2, while proportionally fewer of these women are found in the sectors SETT3, SETT4 AND SETT8. However, for women with A-levels or with university education we find that most of these are in the category QUAL2 (83 per cent) and sector SETT8 (60 per cent). Women in QUAL2 and SETT8 are discriminated against if they have no education or only junior high school education.[26] It is education which substantially improves the

[26] For southern-married females with no or only junior high school with a clerical or teaching job we find that the discrimination coefficient is -0.08 while for the rest it is 0.01 (a statistically significant difference). For this group of women in public administration the discrimination coefficient is -0.08 while for the rest it is 0.004 (again a statistically significant difference).

earnings potential of females with respect to those of males.

Finally, it is of interest to compare our results to those that would obtain when using a stochastic frontier and the Oaxaca method. It is not possible to estimate the stochastic frontier for the southern married female sample as the OLS residuasl are skewed the wrong way (only a reservaton wage frontier can be estimated). However, one can estimatedeteministic frontiers. Doing so for southern marrieds and obtaining the differnce between the frontiers. Doing so for southern marrieds and obtaining the difference between the frontiers (for the hedonic case) calculated using female and male parameters on the female sample give the following discrimination coefficient: Mean = -0.13; Standard Error = 0.003; Range = -0.36 top -0.04. The results are clearly very close to those obtained with the random coefficient model. When we use the Oaxaca method we obtain a discrimination coefficient of -0.02 for the hedonic as well as the reduced form. The negative sign now indicates reverse discrimination.

V CONCLUSION

We use the 1989 Bank of Italy Family survey to analyze wage discrimination between females and males. A random coefficient approach is used to estimate a discrimination coefficient. This method ensures that an earnings frontier is estimated. A further advantage is that the impact of the constant term, education and tenure on discrimination can be assessed separately from the overall discrimination coefficient.

The results show that married females are discriminated against. However, education and tenure, for southern married females, and tenure for northern married females tend to strongly favour potential earnings of women and hence counter-balance the discrimination. An important finding in terms of its policy implications, is that southern-married females without education and tenure would be discriminated against.

The results indicate that it is important to model occupational attachment as the occupational dummies may themselves reflect discrimination. While beyond the scope of this study, future research will need to focus on occupational selectivity.

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