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Discrimination and Equality of Opportunity

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Abstract

This paper presents a measure of social discrimination based on the principle of equality of opportunity. According to this principle we only have to care about the inequality derived from people's differential circumstances (and not about outcome differences due to people's diverse degree of effort). We propose approaching the measurement of group discrimination as the "welfare loss" attributed to the inequality between social groups of similar characteristics. We also provide an empirical application to the analysis of gender discrimination in the European labour market. We estimate wage equations to breakdown wage gaps and to control for extra individual heterogeneity. Given these predictions, we compute the index of welfare loss due to gender discrimination.

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1 Introduction

This paper deals with the measurement of unfairness in income distribution, focusing on the unequal treatment of social groups (what we call *group discrimination*). This kind of analysis involves a mixture of positive and normative economics and has to take into account that agents may be widely heterogeneous in some respects that are relevant for the explanation of outcome differentials (age, education, experience, sector of occupation, labour status, etc.). Disentangling group discrimination from the rewards of differences in agents' *characteristics* (the yields of diverse human capital levels, say) becomes, therefore, a critical modelling choice. This analysis refers to "income" but is actually applicable to the distribution of any unidimensional variable that expresses the individuals' achievements in a society.

We approach the measurement of group discrimination borrowing some ideas from the "equality of opportunity" literature [see Roemer (1993, 1998), Peragine (2000, 2002), Ruiz-Castillo (2003), Villar (2005), Chechi & Peragine (2005)]. According to this approach, one can view income distribution as the result of two different effects: *effort* and *opportunity*. Effort has to do with *responsibility* and refers to the individuals' autonomous decisions (e.g. choice of occupation, investment in human capital, length and intensity of work, healthy lifestyle, etc.). Opportunity refers to the agents' external *circumstances* for which they are not responsible (genes, race, gender, family socioeconomic and cultural background, among others). The equality of opportunity approach implies that a *fair* society should compensate agents for differences in opportunity but not for those differences derived from autonomous choices.[1]

We consider a model of a society with a finite number of agents who can be heterogeneous in several respects, that can be classified as either *characteristics* or *circumstances*. "Characteristics" include those variables related to the market rewards of human capital (e.g. education, experience). They can be mostly understood as an expression of the agents' personal decisions, so they play a role similar to the effort variables in the equality of opportunity literature. By "circumstances" we refer to those features that

[1]Note *autonomous choices* are always relative to the type of social structure under consideration. The education level of an individual, for instance, may quite safely be considered as an effort variable in most contemporary western societies. In other societies, however, may rather reflect the agents' external circumstances (e.g. the family economic, social and cultural background).

cannot be considered responsibility of the agents (e.g. race, gender, family background). We say that two agents belong to the same *social group* if they have the same circumstances, no matter their characteristics. And we define a *category* as a set of agents with the same characteristics, no matter their circumstances. Discrimination refers to the differential outcomes of people within the same category, that is, income differences that are not associated with agents' characteristics but rather with agents' circumstances.

The first part of the paper is devoted to presenting a measure of discrimination that derives from a specific social evaluation function that embodies the equality of opportunity principle and turns out to be additively decomposable. It corresponds to the aggregate welfare loss that derives from the unequal treatment of social groups across the different categories. Let us recall here that the idea of using an additively decomposable measure to allow for a fine assessment of segregation is not new. It appears, among others, in the works of Theil & Finizza (1971), Fuchs (1975) and, much in the spirit of this paper, in Mora & Ruiz Castillo (2003, 2005).

The second part of the paper focusses on gender as a primary instance of people's external circumstances (opportunity), whereas we shall consider variables such as education and experience as the relevant characteristics. Equality of opportunity would require, in this particular context, equalizing the rewards of female and male workers with similar characteristics. We analyze, within this set-up, gender discrimination in the European labour market using data from the European Community Household Panel (1994-2001). Moreover, we use Mincerian wage equations to breakdown wage gaps in differences in returns and differences in individuals' characteristics and/or circumstances. Given these predictions for males and females, we study the index of welfare loss due to gender discrimination treating employment and non employment as a feature defining social groups. Germany, UK and Spain move between 5% and 8% of welfare losses, relative to total welfare, due to gender discrimination during the period, whereas Italy and France are clearly below that level, between 3% and 5%.

2 The model

2.1 Preliminaries: inequality, social welfare, and equality of opportunity

Suppose, to start with, that we want to assess the welfare content of an income distribution in a homogeneous population made of n individuals, by means of a *social evaluation function* $W : \mathbb{R}^n_{++} \to \mathbb{R}$. A standard way of performing this assessment is by using some notion of egalitarian equivalent income. Following Sen (1973) we can define the **egalitarian equivalent income** $x^e(\mathbf{x})$ as the income level such that $W(\mathbf{x}) = W(x^e(\mathbf{x})\mathbf{1}^n)$, where $\mathbf{1}^n$ is the n-vector all whose components are equal to one. That is, $x^e(\mathbf{x})$ is the income level that, if enjoyed by all members of the society, would yield the same social welfare that the actual income distribution. Assuming that the social evaluation function is symmetric and quasi-concave (i.e. anonymous and minimally egalitarian), $x^e(\mathbf{x})$ is always smaller than the actual per capita income, $\mu(\mathbf{x})$. Therefore, we can define an inequality measure I_W by simply computing the difference between perfect equality and the ratio between $x^e(\mathbf{x})$ and $\mu(\mathbf{x})$. That is:

$$I_W(\mathbf{x}) = 1 - \frac{x^e(\mathbf{x})}{\mu(\mathbf{x})}$$

where I_W depends, of course, on the social evaluation function we choose in order to define the egalitarian equivalent income. We can interpret this index, much in the spirit of the Lorenz curve, as a money metric that gives the share of total welfare that is lost as a consequence of the unequal distribution.

The expression above allows one to interpret $x^e(\mathbf{x}) = \mu(\mathbf{x})\,[1 - I_W(\mathbf{x})]$ as the "inequality-adjusted" mean income. Then, a social evaluation function W_I can be naturally defined (for a given inequality measure I) as follows:

$$W_I(\mathbf{x}) = nx^e(\mathbf{x}) = X\,[1 - I(\mathbf{x})]$$

where $X = n\mu(\mathbf{x})$. is the aggregate income. That is, the welfare content of an income distribution vector $\mathbf{x}$ is measured by the *aggregate* inequality-adjusted income. Or, put differently, the welfare evaluation of an income distribution discounts from the aggregate income a fraction $X\,I(\mathbf{x})$ that corresponds to the welfare loss due to inequality. Needless to say, our welfare assessment depends on the inequality index we apply.

Suppose now that the population can be partitioned into k different population subgroups, according to some demographic criterion. When the inequality measure I is *additively decomposable* by population subgroups, we can write:

$$W_I(\mathbf{x}) = X - X\sum_{j=1}^{k}\omega_j(.)I(\mathbf{x}^j) - X\,I\left[\mu(\mathbf{x}^1)\mathbf{1}^1, ..., \mu(\mathbf{x}^k)\mathbf{1}^k\right] \qquad [1]$$

This expression tells us that the welfare evaluation of distribution $\mathbf{x}$ is measured by the corresponding total income, deflated by two different terms. The first one, $X\sum_{j=1}^{k}\omega_j(.)I_W(\mathbf{x}^j)$, describes the aggregate welfare loss that is due to the inequality *within* the corresponding population subgroups. Here the terms $\omega_j(.) > 0$ are the coefficients that determine the relative weight of each population subgroup. The second term of discount, $XI_W\left(\mu(\mathbf{x}^1)\mathbf{1}^1, ..., \mu(\mathbf{x}^k)\mathbf{1}^k\right)$, measures the welfare loss due to the inequality *between* population subgroups (measured by the dispersion of the mean income of the groups weighted by the corresponding population size).

Consider now a society consisting of $N = \{1, 2, ..., n\}$ individuals that can be classified into $g = 1, 2, ..., G$ *social groups*, where a *group* describes the set of agents with the same external circumstances. A *category* is a collection of individuals with similar characteristics. There are C different categories, that are indexed by c. A *cell* describes a set of agents of the same group with the same characteristics. That is, cell (c, g) is the set of agents of group g who belong to category c. There are n_{cg} agents in cell (c, g) whose income vector is $\mathbf{x}(c, g)$. *Category* c, denoted by $N(c)$, consists of those agents in N, no matter their social groups, who have the same characteristics. There are $n_c = \sum_{g=1}^{G} n_{cg}$ agents in category c with income $\mathbf{x}(c) = [\mathbf{x}(c, 1),\ ...,\ \mathbf{x}(c, G)]$, for $c = 1, 2, ..., C$. An *Income Allocation* is a point $\mathbf{x} \in \Pi_{c=1}^{C}\mathbb{R}_{++}^{n_c}$. That is, x_{ic} describes the income of an agent $i \in N(c)$. Let $X_c = \sum_{i\in N(c)} x_{ic}$, for each $c = 1, 2, ..., C$. That is, X_c is the total income corresponding to those agents in category $N(c)$.

We want to measure the welfare content of an income allocation from the equality of opportunity viewpoint. This principle establishes that the inequality between categories is not ethically relevant. When the evaluation formula is additively decomposable, equation [1] and the equality of opportunity principle permits one to define the following welfare measure:

$$\begin{aligned} V_I(\mathbf{x}) \quad : \quad &= W_I(\mathbf{x}) + X\, I\left[\mu(\mathbf{x}^1)\mathbf{1}, ..., \mu(\mathbf{x}^C)\mathbf{1}\right] \\ &= X\left[1 - \sum_{c=1}^{C} \omega_c(.) I(\mathbf{x}^c)\right] \qquad [2] \end{aligned}$$

That is, we discard that part of the observed inequality that is due to the differences in agents' characteristics.

2.2 A closed evaluation formula

Equation [2] allows for a number of alternative specifications, depending on the additively decomposable inequality index we choose. Let us consider now some standard requirements that will lead to a closed evaluation formula.

Our first requirement is that the coefficients that determine the weight of the population subgroups in the within term of the decomposition in equation [1] add up to one; that is, $\sum_{c=1}^{C} \omega_c(.) = 1$. When this is the case, we have an exact decomposition of the inequality index and the interpretation of [1] is much simpler and intuitive, because the within groups component is just a weighted average of the inequality of the different categories. Moreover, the between groups component is not independent of those weights when $\sum_{c=1}^{C} \omega_c(.) \neq 1$ (Cf. Theil (1967, p. 125)).

Define now a *regular* inequality index as one that satisfies the following basic properties: symmetry (permuting incomes does not change the value of the index), population replication (replicating a given population does not change the value of the index), Dalton's principle of transfers (a *small* transfer from a rich to a poor reduces inequality), and zero homogeneity ($I(\lambda\mathbf{x}) = I(\mathbf{x})$ for all $\lambda > 0$). We know from Shorrocks (1980) that any regular and smooth (differentiable) inequality index that is additively decomposable is a member of the generalized entropy family I_θ. Moreover, if we require an exact decomposition of the within groups term we are left with just two members of the family: the first index of Theil, T, that corresponds to the value $\theta = 1$ in the entropy family, and the second index of Theil, T^*, that corresponds to $\theta = 0$.

So, if we construct a social evaluation function out of a regular inequality index and require this index to satisfy additive decomposability plus exact decomposition, our evaluation formula is reduced to just two possibilities: $W_T(\mathbf{x}) = X[1 - T(\mathbf{x})]$ and $W_{T^*}(\mathbf{x}) = X[1 - T^*(\mathbf{x})]$. The main difference between those two indices is that the role of population and income shares is reversed. In the decomposition corresponding to the first index of Theil the coefficients $\omega_c(.)$ correspond to income shares whereas in the case of the second index they correspond to population shares.

Let $f_{ic}(\mathbf{x}) = \frac{\partial W(\mathbf{x})}{\partial x_{ic}}$ be the *marginal social value of agent* i in category c with income x_{ic}. We say that the evaluation function W satisfies the property of *minimal equity* (Sen (1973), Villar (2005)) when $x_{ic} > x_{hc}$ implies $f_{ic}(\mathbf{x}) < f_{hc}(\mathbf{x})$, for each given category c. That is, it is satisfied when we give more weight in social welfare to those agents with smaller incomes, within each category. It is easy to see that the first index of Theil satisfies this property whereas the second one does not.

We can therefore summarize the above discussion as follows:

Theorem 1 *Let $W_I : \mathbb{R}_{++} \rightarrow \mathbb{R}$ be a Social Evaluation Function obtained out of a regular and smooth inequality index. W_I satisfies minimal equity and exact additive decomposability if and only if, for all $\mathbf{x} \in \mathbb{R}^n_{++}$,*

$$W_I(\mathbf{x}) = X\left[1 - T(\mathbf{x})\right] \qquad [3]$$

where $T(\mathbf{x})$ is Theil's first index of inequality.[2]

It is easy to see that the associated equality of opportunity welfare measure is given by:

$$V(\mathbf{x}) = \sum_{c=1}^{C} X_c\left[1 - T(\mathbf{x}(c))\right] \qquad [2']$$

Therefore, we are measuring the welfare content of an income allocation $\mathbf{x}$ as the aggregate income of all groups, each of which is deflated by inequality, measured by the Theil's first inequality index. Each term $X_c T(\mathbf{x}(c))$ gives us the aggregate welfare loss that is due to the unequal distribution of income in category c. See Villar (2005) for an alternative characterization of this formula.

[2] Let us recall here that Theil's (first) inequality index is given by: $T(x)) = \frac{1}{n}\sum_{i=1}^{n} \frac{x_i}{\mu(\mathbf{x})} \ln\left(\frac{x_i}{\mu(\mathbf{x})}\right)$. This index can be interpreted as a measure of the distance between population shares and income shares [see Theil (1967)].

2.3 Discrimination as a social welfare loss

Let us consider the measurement of inequality of opportunity and group discrimination that derive from the evaluation formula [2′]. We first determine the welfare loss due to the inequality of opportunity (the size of unequal distribution across categories), and then define a simple discrimination index. To do that we apply once more the decomposability properties of the social evaluation function.

Let each term $X_c [1 - T [\mathbf{x}(c)]]$ in equation [2′] be considered as the welfare measure of income allocation $\mathbf{x}(c)$ for the category $N(c)$, considered as an independent society, $c = 1, 2, ..., C$. Recurring once more to the decomposability property of the index, taking the constituent groups as the relevant partition, we can write:

$$X_c [1 - T [\mathbf{x}(c)]] = \sum_{g=1}^{G} X_{cg}[1 - T(\mathbf{x}(c, g))] - Q [\mathbf{x}(c)] \qquad [4]$$

where $\mathbf{x}(c, g)$ is the income vector of the (c, g) cell, X_{cg} its aggregate income, for $g = 1, 2, ..., G$, $T(\mathbf{x}(c, g))$ the corresponding inequality index, and:

$$Q_c(\mathbf{x}) = \sum_{g=1}^{G} X_{cg} \ln \frac{\mu(c, g)}{\mu(c)}$$

is the *between cells* inequality in category c. This expression gives us an *overall* measure of the welfare loss due to the inequality of opportunity, attributed to category c, as a weighted sum of the relative means (in logs) of the different groups. Note that $Q_c(\mathbf{x}) \geq 0$, with $Q_c(\mathbf{x}) = 0$ if and only if $\mu(c, g) = \mu(c)$ for all g.

By introducing this expression into [2′] we get:

$$V(\mathbf{x}) = \sum_{c=1}^{C} \sum_{g=1}^{G} X_{cg}[1 - T(\mathbf{x}(c, g))] - \sum_{c=1}^{C} \sum_{g=1}^{G} X_{cg} \ln \frac{\mu(c, g)}{\mu(c)} \qquad [5]$$

This equation tells us that the total welfare associated with the allocation $\mathbf{x}$ can be understood as the sum of the welfare of all cells that compose the society discounted by the term:

$$Q(\mathbf{x}) := \sum_{c=1}^{C} \sum_{g=1}^{G} X_{cg} \ln \frac{\mu(c, g)}{\mu(c)} \qquad [6]$$

which gives us the *aggregate welfare loss* due to inequality of opportunity. This welfare loss consists of a weighted sum of the mean deviations of the cells with respect to their corresponding categories, where the weights are given by the corresponding aggregate incomes. Note that $\ln \frac{\mu(c,g)}{\mu(c)}$ will be negative when $\mu(c,g) < \mu(c)$ and positive otherwise. Therefore, those cells with mean income above that of their category reduce total welfare whereas those cells with mean income below their category increase it.

It is worth stressing that Q is a remarkably simple and intuitive measurement function which does not require much information to be computed (in particular it does not require information about the entire distribution!). For a given income allocation $\mathbf{x} \in \mathbb{R}^n_{++}$, $Q(\mathbf{x})$ tells us the total income that society is losing as a consequence of the inequality of opportunity. Function Q is a *money metric* and, therefore, our welfare assessment will depend on the units in which income is measured.

We now define our measure of welfare loss due to discrimination, $L(.)$, as follows:

$$L(\mathbf{x}) = \frac{Q(\mathbf{x})}{V(\mathbf{x})} \times 100 \qquad [7]$$

That is, $L(\mathbf{x})$ tells us the percentage of total welfare that is lost due to discrimination.

Computing this measure requires a precise knowledge of the whole income distribution vector. This might be hard to obtain in some empirical applications. Note, however, that this complication would vanish if all agents within a given cell had the same income (something that will have to be assumed in many empirical applications). Indeed, if $x_{ic} = \mu(c,g)$ for all $i \in N(c)$, we have $T(\mathbf{x}(c,g)) = 0$ and, therefore, the formulae above become, respectively:

$$\widehat{V}(\mathbf{x}) = X - Q(\mathbf{x}) \qquad [5']$$

$$\widehat{L}(\mathbf{x}) = \frac{Q(\mathbf{x})}{X - Q(\mathbf{x})} \times 100 \qquad [7']$$

These formulae are reasonable approximations to the measurement of total welfare and the relative welfare loss due to the inequality of opportunity, that do not require information on the whole income distribution vector. Needless to say the accuracy of this approximation depends on the size of the cells (the finer the grid the closer to its real value).

Remark *The measure of welfare loss due to inequality of opportunity is an aggregate measure of the effects of discrimination on social welfare. Note that it is the sum of positive and negative entries, depending on the relative means of the cells, so that it has the nature of a net global index.*

3 An application: Gender discrimination in the European labour market

3.1 Gender discrimination in the labour market

Let us now consider the case of gender discrimination in the labour market as a specially relevant instance of group discrimination. We aim at evaluating the welfare content of the labour income distribution by taking women and men as the reference social groups and applying the decomposability properties presented above. In this way we generate a measure of gender discrimination that corresponds to the welfare loss associated with the inequality between women and men, aggregated across categories. Gender discrimination is captured by the sum of the unexplained income dispersion between those categories of female and male workers with similar characteristics.

The measurement of gender discrimination by means of this formula amounts to assuming that a labour income allocation is fair whenever all people within the same category receive the same income. And, consequently, those differences due to diverse characteristics are not to be considered gender discrimination at the labour market.[3] Therefore, choosing the variables that define social groups and categories amounts to determine the kind of discrimination we capture and the kind of income dispersion we disregard. A point in case is that concerning employed and non-employed working age population, where we call *non-employed* the union of unemployed and inactive. Using employed and non-employed workers as *characteristics* implies cancelling the inequality due to the differences in participation between women and men (as we would be attributing that inequality to differences between employed and non-employed, and not between female and male workers). If, on the contrary, we think of employed and non-employed as defining the social groups, the welfare loss will capture simultaneously the differences in

[3]It would be much more accurate saying that this is not part of income discrimination. In fact it may well be that discrimination occurs at deeper and more fundamental levels.

salaries, unemployment, and participation rates. We favour here the last approach because we understand that non-employment differentials between women and men derive more from economic and social restrictions than from free choices.

3.2 Data and results

We apply here this way of modelling gender discrimination to the analysis of the labour market in five European countries with comparable datasets: Germany (de), Spain (es), France (fr), the United Kingdom (uk) and Italy (it). The time span considered is 1994-2001. Nevertheless, the data of Germany present a "hole" in 1998 and the one for the UK are only available for 1994-1997. The data source comes from two different datasets. Data on population and employment status comes from the EU Labour Force Survey, offered by Eurostat. Data on wages are obtained from the European Community Household Panel (hereafter 'ECHP'). We have measured average hourly wages for each worker by using individual data coming from the ECHP eight available waves, 1994 to 2001.

In this application we consider four social groups: women and men, employed or not.[4] Individual categories are defined by two variables. The first one is *education* that simply generates two categories: "low" educated workers (meaning those with the mandatory level of education in each country) and "high" educated workers (those with more than the mandatory education). The second one is *age*, considered as a proxy of experience; here we consider three different categories: young, medium, and old workers. We have therefore six categories and four social groups within each category in this exercise.

We compute the index of welfare loss due to gender discrimination for each cell by using equation (6). Moreover, we get a unit-free measure by considering the welfare loss per unit of welfare, due to gender discrimination. Hence, we compute the index $\hat{L}(\mathbf{x})$ in equation $(7')$.

Those individuals who are not employed, that is who are unemployed or inactive, enter the data with a notional income that is computed according to each country's specific institutional definition. More precisely, for

[4] That is, we do not treat non-employment as a personal choice but rather as part of the agents' "circumstances". The data we obtain are to be interpreted, consequently, as an upper bound of gender discrimination.

unemployed people we compute their income by using each country's Unemployment Benefits system, controlling for the duration in unemployment in each cell (as Unemployment Benefits in all countries analyzed depend on such duration). And we impute an income equal to the mean Social Protection Benefits, measured by the OECD, for those who are not in the labor force.[5] Note that in this way we reduce the inequality between employed and non-employed due to inactive people.

Figure 1 summarizes the first result of this analysis. It depicts the index of welfare loss due to gender discrimination based on the observed differences in hourly wages. Germany, UK and Spain experience a relative welfare loss that oscillates between 5% and 8% during the period. Italy and France are clearly below that level (somewhere between 3% and 5%). It is quite noticeable the idiosyncratic nature of the corresponding time paths.

But the analysis in that figura is still quite preliminary as there is much more heterogeneity among women and men than that captured in that classification of workers' social groups and categories. Think of aspects such as tenure on the job, occupation type, economic sector, size of the firm, etc. All of them are widely recognized as important determinants of wage differentials. One way of incorporating this additional heterogeneity into the model is to supplement the analysis developed above with some econometric estimations. One can also think of defining a finer partition of social groups and characteristics. Yet some of those aspects that explain wage differentials are difficult to attribute to one or another dimension. That is where the econometrics plays a role allowing us to control for that heterogeneity.

Hence, we specify wage equations following the traditional Mincerian approach (Mincer, 1974). The observations on the dependent variable, hourly wages, will be classified into two regimes that are generated by different probability laws with the following mean, in log terms:

$$\ln W_j = X_j \beta_j + u_j \qquad with\ j = man,\ woman$$

where W_j represents observed hourly wages for a men or women, X_j is the set of observable determinants of wages and u_j represents the unobservable component of wages, which is assumed to be normally distributed with mean zero and variance σ_j. We will consider in X_j all relevant observed differences between men and women, regardless they could be considered as charac-

[5] These benefits are measured in annual terms. Hence we use the annual mean hours in each cell, obtained from the ECHP, to obtain potential hourly benefits for inactive people.

teristics or as circumstances. In Tables 1-5 we can see the results for the estimations for each of the five studied countries.[6] The variables considered in those equations are tenure in the job, occupation category in that job, some characteristics of the firm (size, sector of activity, region, public ownership), marital status of the worker, number of children and some characteristics of the spouse (labour status and his/her educational level).

Hence, we estimate a different equation for each gender in each labour category and use it to breakdown predicted wage gaps into differences in returns and differences in individuals' characteristics and/or circumstances (See Oaxaca, 1973). As it is well known, the former difference, the one in returns, is what is known as differences due to discrimination in the labour market. Moreover, we can decompose predicted wages in two different ways, basically depending on the counterfactual prediction we use:

$$\begin{aligned}\hat{w}_M - \hat{w}_F = \bar{x}_M\hat{\beta}_M - \bar{x}_F\hat{\beta}_F &= \bar{x}_M\left(\hat{\beta}_M - \hat{\beta}_F\right) + \hat{\beta}_F\left(\bar{x}_M - \bar{x}_F\right) \\ &= \bar{x}_F\left(\hat{\beta}_M - \hat{\beta}_F\right) + \hat{\beta}_M\left(\bar{x}_M - \bar{x}_F\right)\end{aligned}$$

In the first case, we are using a counterfactual prediction for females (the wage they had earned in case their characteristics/circumstances were the ones of males) and in the second case the counterfactual prediction is built for males (the wage they had earned in case their characteristics/circumstances were paid using the coefficients estimated for females). As we can see in Figures 3 and 4, the decomposition using women's counterfactuals can be considered as a maximum limit of the welfare loss index whereas the one which uses men counterfactuals represent a minimum level for such index. The reason is that women's counterfactual is lower than the one for men.

Finally, before going to the results, we have to say that, as it is usual, we could control for selection into employment, in our wage equations. It is obvious that men and women employed are not a random sample of men and women in the labour market. The usual way of controlling this self-selection problem is considering Heckman (1979) corrections in the wage equations. We do not want to control for this, however, as we consider that employment

[6] As we are considering six labour categories for this application, we are in fact estimating six equations for each country. For the sake of space we are showing in these tables only the results for the total sample in each gender in each country. The results for each labour group are highly similar in the estimated coefficients with those shown in the table (even though, of course, the estimated coefficients are less significant).

is an economic trait determining two different social groups. In this sense, we want to compare wages for employed men and women, without such a correction (otherwise we would lose a crucial source of discrimination we are interested in).

Hence, going directly to our results, Figure 2 presents the results for the welfare loss index based on these econometric approach, that is, based on predicted wages instead of observed wages as they are in Figure 1. As we can see comparing both figures, the welfare loss index based on predicted wages is almost equal to the one based on observed wages. However, we have that the one based on predicted wages is a bit smaller for Germany and the UK whereas it is larger for Italy and France than the one based on observed wages. Figures 5 to 11 summarize our main findings. They show the comparative evolution of this index for the five selected countries both for the whole economy and for the different groups defined by their employment status, education, and age.

Figures 5 and 6 describe the welfare loss due to gender discrimination by education levels. Two features are worth stressing. First, that we find also here very different national patterns. Second, that gender discrimination is relatively higher within highly educated workers only for Spain and Italy: they account for more than 50 % of total discrimination in both countries and during all the years considered. On the contrary, France and specially Germany and the UK show more welfare losses due to gender discrimination for low educated workers.

Figures 7 to 9 present the results for the age groups. The diversity of patterns between countries is also a relevant feature. The strongest discrimination occurs within the old workers group, with some differences. Spain is the country where welfare loss due to gender discrimination is mainly based on the discrimination among old workers (almost 60% of the total index).

Finally, Figure 10 shows the results for employed people and Figure 11 the ones for non-employed. The levels of welfare loss due to gender discrimination among non-employed workers decrease substantially, showing the relevance of computing or not non-employment discrimination. The countries' indexes move between 0.02 and 0.06 of welfare loss given by gender discrimination among employed workers. It is worth stressing that the behavior of the four countries is quite diverse along the years. The discrimination for employed workers is more important although it shows a more stable pattern, with Spain showing an increasing trend which is totally offset by the highly decreasing pattern of the discrimination index among the non-employed.

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TABLE 1: Regression Results for Spain (EHCP, Full sample, 1994-2001)

	MALES			FEMALES		
	Coef.	Std. Dev.	T Statistic	Coef.	Std. Dev.	T Statistic
Unskilled	-0,1707	0,0062	-27,71	-0,2186	0,0099	-22,13
Tenure	0,0299	0,0015	20,22	0,0447	0,0021	21,16
Tenure (sq)	-0,0009	0,0001	-12,48	-0,0016	0,0001	-15,81
High. Ocup.	0,5830	0,0164	35,62	0,5881	0,0361	16,31
Med-High Ocup.	0,2438	0,0093	26,3	0,2679	0,0125	21,49
Medium Ocup.	0,1548	0,0120	12,86	0,1308	0,0138	9,46
Med-Low Ocup.	0,0426	0,0078	5,48	0,0597	0,0132	4,52
Married	0,1779	0,0110	16,24	0,1013	0,0183	5,54
No. Children	0,0262	0,0030	8,88	0,0089	0,0047	1,87
Age	0,0370	0,0018	21,01	0,0469	0,0028	16,56
Age (sq.)	-0,0003	0,0000	-16,59	-0,0005	0,0000	-14,05
Public Sector	0,1542	0,0069	22,25	0,2712	0,0093	29,3
Spouse Prim. Edu.	-0,1965	0,0090	-21,76	-0,1813	0,0121	-15
Spouse Second. Edu.	-0,0754	0,0100	-7,56	-0,0788	0,0133	-5,9
Agriculture	-0,1731	0,0128	-13,57	-0,0357	0,0277	-1,29
Industry	0,1065	0,0061	17,5	0,0307	0,0111	2,77
Spouse employed	-0,0347	0,0067	-5,15	0,0198	0,0148	1,33
Overskilled	-0,0209	0,0052	-4,02	-0,0307	0,0077	-3,96
Medium-size firm	0,0887	0,0063	14,08	0,1621	0,0092	17,62
Big Firm	0,1936	0,0063	30,68	0,1646	0,0094	17,49
Constant Term	5,9999	0,0342	175,49	5,5559	0,0538	103,31
Number Observations		21464			10975	
R-squared		0,5489			0,5607	

TABLE 2: Regression Results for France (EHCP, Full sample, 1994-2001)

	MALES			FEMALES		
	Coef.	Std. Dev.	T Statistic	Coef.	Std. Dev.	T Statistic
Unskilled	-0,1515	0,0070	-21,76	-0,2032	0,0088	-23,21
Tenure	0,0244	0,0018	13,85	0,0358	0,0021	16,93
Tenure (sq)	-0,0007	0,0001	-8,28	-0,0009	0,0001	-9,19
High. Ocup.	0,5365	0,0171	31,36	0,5045	0,0245	20,6
Med-High Ocup.	0,3083	0,0129	23,86	0,3153	0,0136	23,1
Medium Ocup.	0,1277	0,0154	8,27	0,1995	0,0139	14,32
Med-Low Ocup.	0,0715	0,0127	5,64	0,0909	0,0160	5,69
Married	0,2552	0,0120	21,22	0,1460	0,0178	8,19
No. Children	-0,0018	0,0029	-0,64	-0,0198	0,0042	-4,73
Age	0,0516	0,0026	19,69	0,0480	0,0034	14,16
Age (sq.)	-0,0005	0,0000	-15,89	-0,0005	0,0000	-12,28
Public Sector	0,1334	0,0077	17,25	0,1529	0,0083	18,36
Spouse Prim. Edu.	-0,1915	0,0098	-19,49	-0,2036	0,0119	-17,14
Spouse Second. Edu.	-0,1436	0,0097	-14,82	-0,1804	0,0114	-15,84
Agriculture	-0,1476	0,0243	-6,08	-0,0811	0,0418	-1,94
Industry	0,1119	0,0070	16,07	0,0879	0,0106	8,29
Spouse employed	-0,0432	0,0075	-5,73	-0,0045	0,0140	-0,32
Overskilled	0,0165	0,0059	2,81	-0,0233	0,0071	-3,29
Medium-size firm	0,0022	0,0104	0,21	0,0206	0,0133	1,55
Big Firm	0,0882	0,0092	9,54	0,0619	0,0127	4,86
Constant Term	2,7436	0,0497	55,22	2,8652	0,0621	46,13
Number Observations		17656			13268	
R-squared		0,457			0,394	

TABLE 3: Regression Results for Germany (EHCP, Full sample, 1994-1997 & 1999-2001)

	MALES			FEMALES		
	Coef.	Std. Dev.	T Statistic	Coef.	Std. Dev.	T Statistic
Unskilled	-0,1818	0,0067	-27,28	-0,1830	0,0083	-22,1
Tenure	0,0010	0,0004	2,61	0,0071	0,0005	13,99
Tenure (sq)	0,0000	0,0000	1,8	0,0000	0,0000	12,9
High. Ocup.	0,3643	0,0141	25,81	0,3359	0,0241	13,91
Med-High Ocup.	0,2631	0,0106	24,88	0,2368	0,0132	17,87
Medium Ocup.	0,1748	0,0132	13,28	0,2259	0,0142	15,96
Med-Low Ocup.	0,0667	0,0102	6,55	0,0452	0,0142	3,18
Married	0,1640	0,0112	14,66	0,0528	0,0155	3,4
No. Children	-0,0072	0,0027	-2,7	-0,0430	0,0039	-10,99
Age	0,1101	0,0017	64,4	0,1222	0,0023	52,09
Age (sq.)	-0,0012	0,0000	-58,14	-0,0014	0,0000	-47,33
Public Sector	0,0904	0,0067	13,48	0,1963	0,0070	27,95
Spouse Prim. Edu.	-0,0660	0,0095	-6,95	-0,0409	0,0128	-3,2
Spouse Second. Edu.	-0,0625	0,0077	-8,11	-0,0757	0,0082	-9,19
Agriculture	-0,1338	0,0189	-7,06	-0,1764	0,0272	-6,48
Industry	0,1128	0,0058	19,42	0,0839	0,0083	10,12
Spouse employed	-0,0668	0,0060	-11,16	-0,0371	0,0114	-3,26
Medium-size firm	0,0924	0,0059	15,56	0,1071	0,0073	14,76
Big Firm	0,2027	0,0065	31,04	0,2192	0,0088	24,8
Constant Term	0,6554	0,0353	18,55	0,2862	0,0458	6,25
Number Observations		29043			19839	
R-squared		0,4886			0,3994	

TABLE 4: Regression Results for Italy (EHCP, Full sample, 1994-2001)

	MALES			FEMALES		
	Coef.	Std. Dev.	T Statistic	Coef.	Std. Dev.	T Statistic
Unskilled	-0,0914	0,0050	-18,21	-0,1392	0,0076	-18,31
Tenure	0,0161	0,0013	12,5	0,0138	0,0017	8,3
Tenure (sq)	-0,0005	0,0001	-8,34	-0,0004	0,0001	-5,41
High. Ocup.	0,5525	0,0137	40,32	0,4344	0,0383	11,36
Med-High Ocup.	0,1963	0,0078	25,04	0,2485	0,0108	23,08
Medium Ocup.	0,1208	0,0082	14,78	0,1198	0,0106	11,32
Med-Low Ocup.	0,0391	0,0068	5,75	0,0367	0,0105	3,49
Married	0,2180	0,0114	19,13	0,1182	0,0160	7,41
No. Children	0,0285	0,0026	10,82	0,0017	0,0037	0,47
Age	0,0257	0,0016	15,96	0,0236	0,0023	10,29
Age (sq.)	-0,0002	0,0000	-12,18	-0,0002	0,0000	-6,51
Public Sector	0,0932	0,0053	17,6	0,1731	0,0072	24,11
Spouse Prim. Edu.	-0,2161	0,0096	-22,52	-0,1783	0,0109	-16,34
Spouse Second. Edu.	-0,1259	0,0090	-13,98	-0,1169	0,0102	-11,43
Agriculture	-0,1250	0,0109	-11,48	-0,2162	0,0184	-11,77
Industry	0,0028	0,0052	0,54	0,0133	0,0081	1,64
Spouse employed	-0,0433	0,0053	-8,19	0,0482	0,0109	4,44
Overskilled	-0,0027	0,0042	-0,65	0,0040	0,0056	0,72
Medium-size firm	0,0654	0,0052	12,48	0,0839	0,0069	12,1
Big Firm	0,0959	0,0052	18,37	0,0790	0,0077	10,28
Constant Term	2,0025	0,0320	62,65	1,9139	0,0435	43,99
Number Observations		21222			12708	
R-squared		0,4643			0,4939	

TABLE 5: Regression Results for the U.K. (EHCP, Full sample, 1994-1997)

	MALES			FEMALES		
	Coef.	Std. Dev.	T Statistic	Coef.	Std. Dev.	T Statistic
Unskilled	-0,1604	0,0068	-23,63	-0,1796	0,0073	-24,45
Tenure	0,0312	0,0018	17,63	0,0281	0,0020	14,34
Tenure (sq)	-0,0013	0,0001	-14,45	-0,0011	0,0001	-11,33
High. Ocup.	0,4985	0,0140	35,72	0,4730	0,0170	27,85
Med-High Ocup.	0,3928	0,0131	29,88	0,2927	0,0143	20,46
Medium Ocup.	0,1568	0,0148	10,63	0,2341	0,0144	16,3
Med-Low Ocup.	0,1248	0,0126	9,91	0,0366	0,0158	2,31
Married	0,1788	0,0124	14,39	0,0940	0,0168	5,58
No. Children	-0,0087	0,0033	-2,62	-0,0671	0,0038	-17,56
Age	0,0777	0,0020	39,24	0,0845	0,0023	36,69
Age (sq.)	-0,0009	0,0000	-36,59	-0,0010	0,0000	-35,5
Public Sector	0,0883	0,0082	10,71	0,2060	0,0076	26,97
Spouse Prim. Edu.	-0,1058	0,0088	-12,02	-0,1521	0,0092	-16,44
Spouse Second. Edu.	-0,0542	0,0101	-5,35	-0,0923	0,0109	-8,49
Agriculture	-0,1679	0,0286	-5,87	-0,1908	0,0570	-3,35
Industry	0,0827	0,0068	12,16	0,1232	0,0098	12,57
Spouse employed	-0,0529	0,0086	-6,18	-0,0255	0,0140	-1,82
Medium-size firm	0,0672	0,0081	8,27	0,0715	0,0086	8,32
Big Firm	0,1885	0,0070	26,88	0,1833	0,0076	24,08
Constant Term	0,1933	0,0388	4,99	0,1062	0,0433	2,45
Number Observations		19333			16519	
R-squared		0,4488			0,3966	

Figure 1: Index using observed data

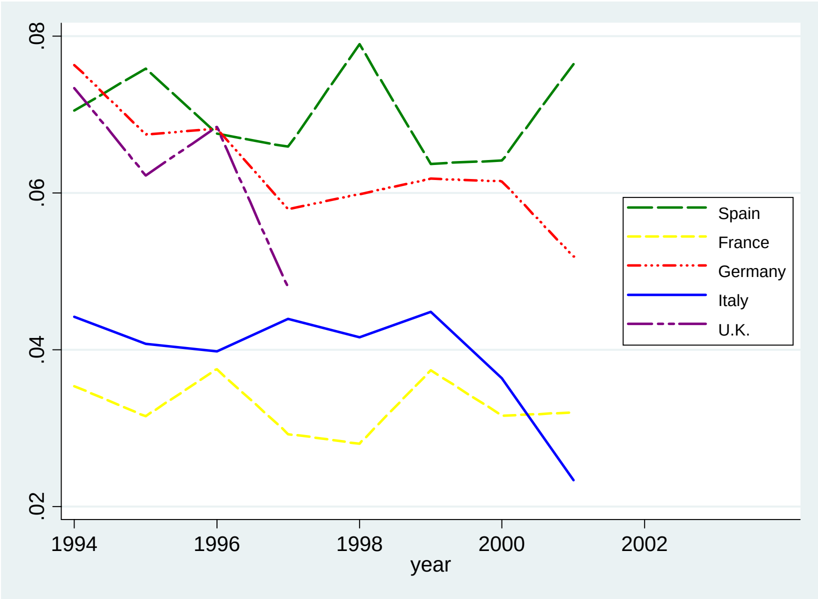

Figure 2: Index using predicted wages

.

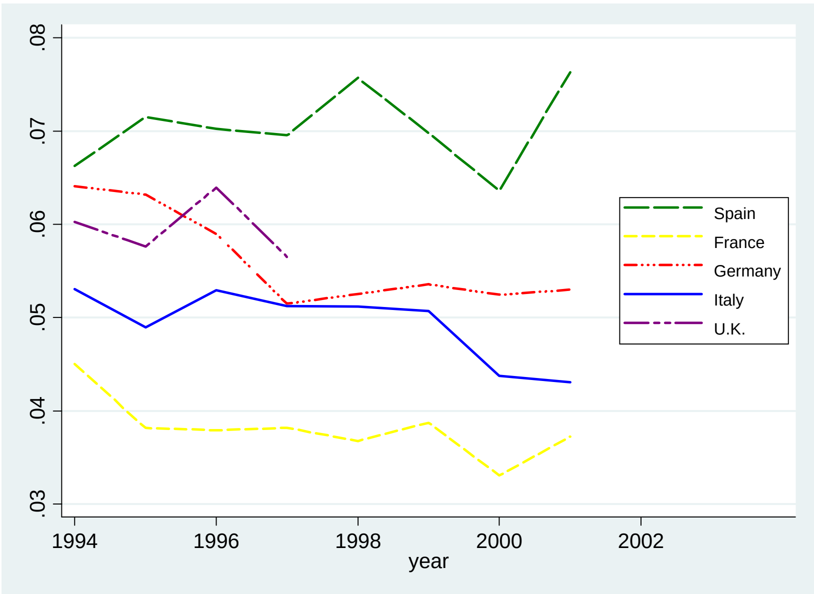

Figure 3: Index using as counterfactual the returns to women applied to men (MAXIMUM)

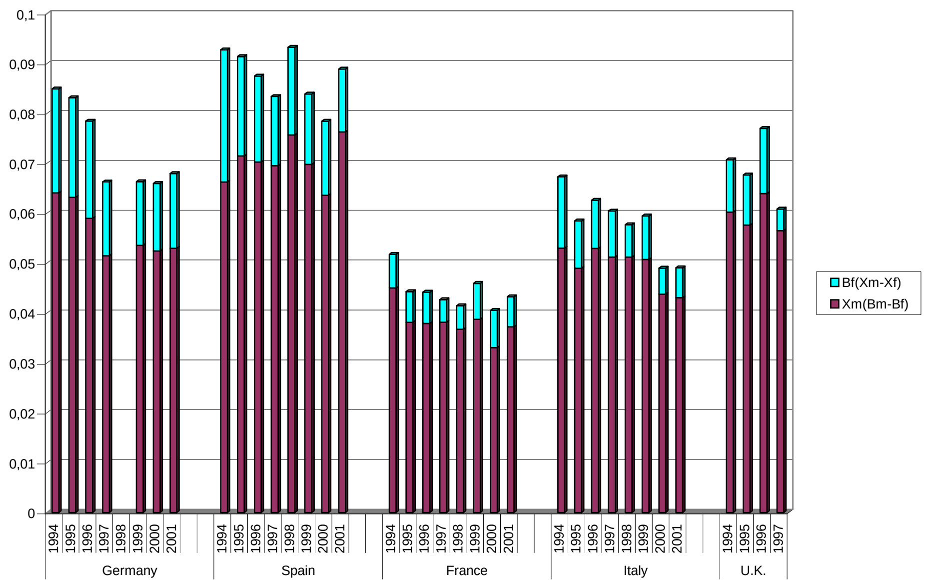

Figure 4: Index using as counterfactual the returns to men applied to women (MINIMUM)

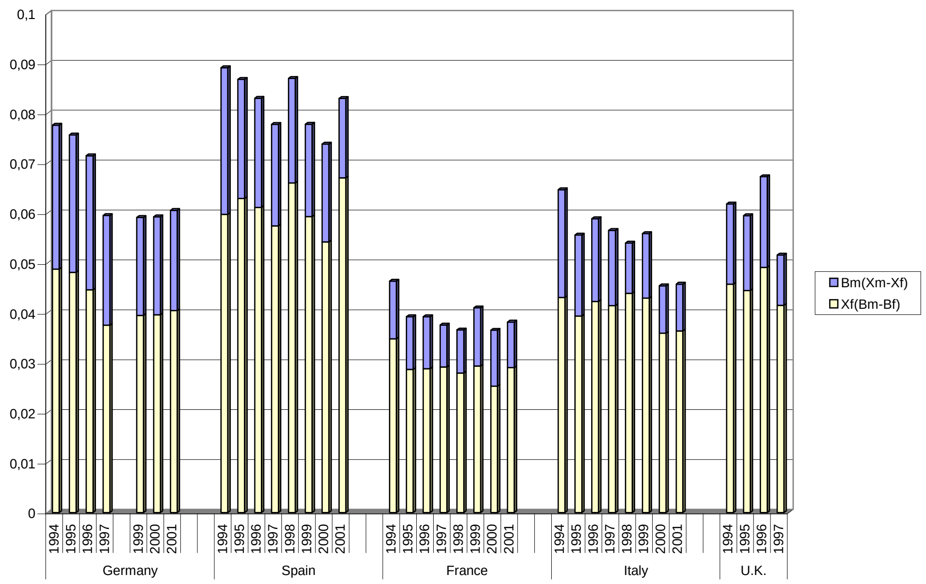

Figure 5: Index for Skilled workers (using as counterfactual the returns to men applied to women)

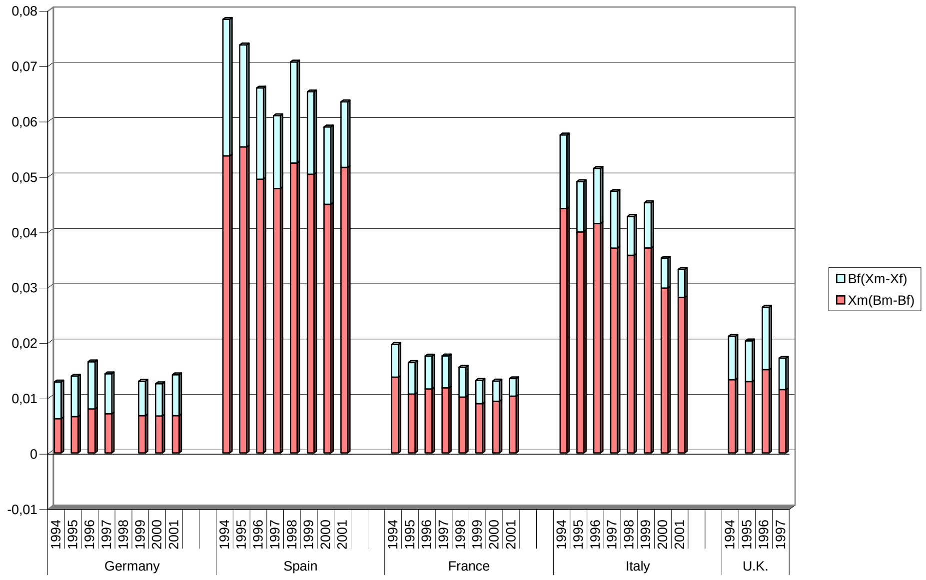

Figure 6: Index for Unskilled workers (using as counterfactual the returns to men applied to women)

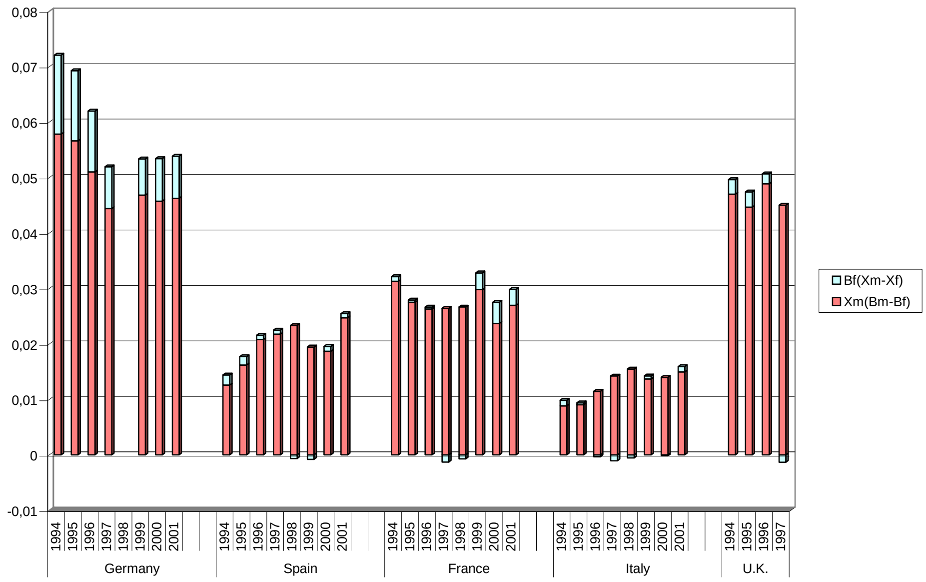

Figure 7: The welfare loss due to gender discrimination within the young (differences in returns using women's counterfactuals)

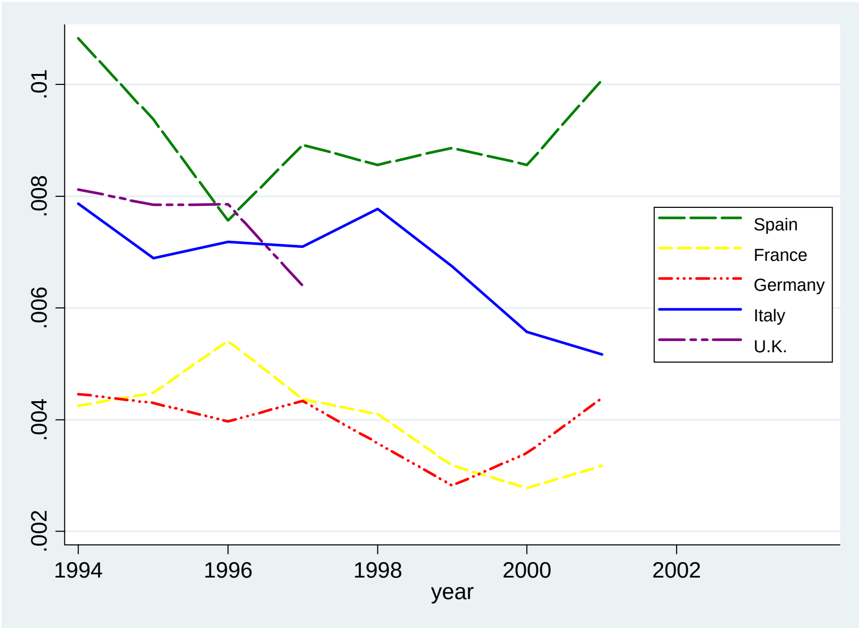

Figure 8: The welfare loss due to gender discrimination within the medium aged population (differences in returns using women's counterfactuals)

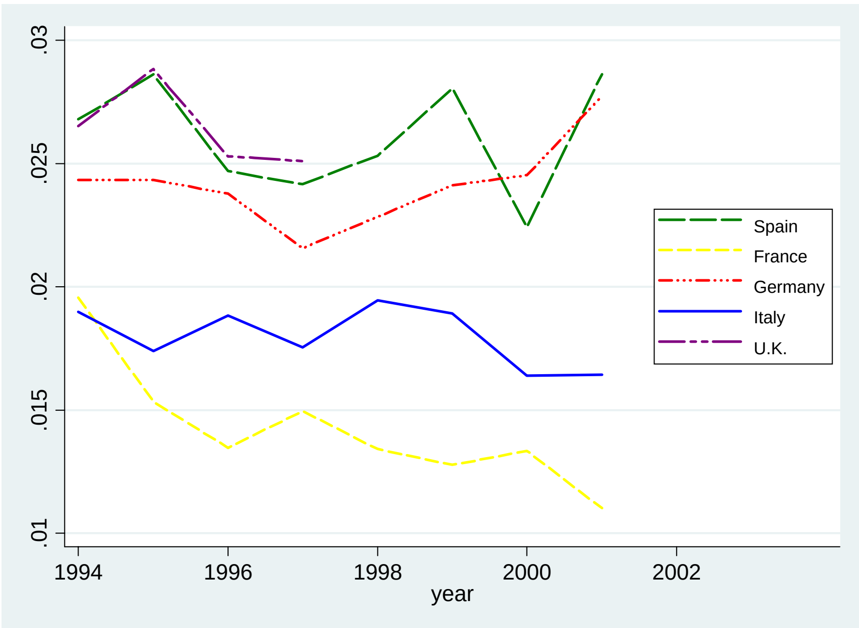

Figure 9: The welfare loss due to gender discrimination within the old (differences in returns using women's counterfactuals)

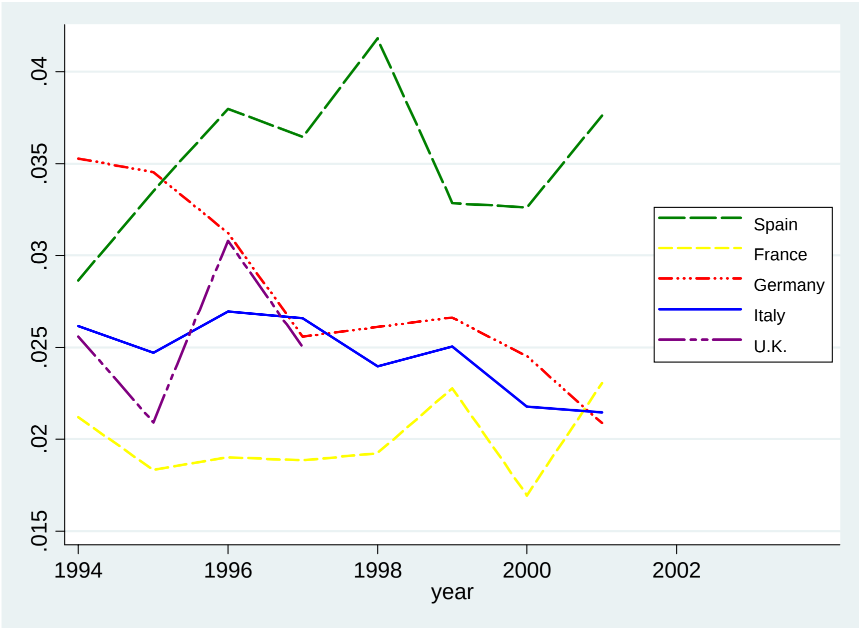

Figure 10: Welfare loss due to gender discrimination in the employed population (differences in returns using women's counterfactuals)

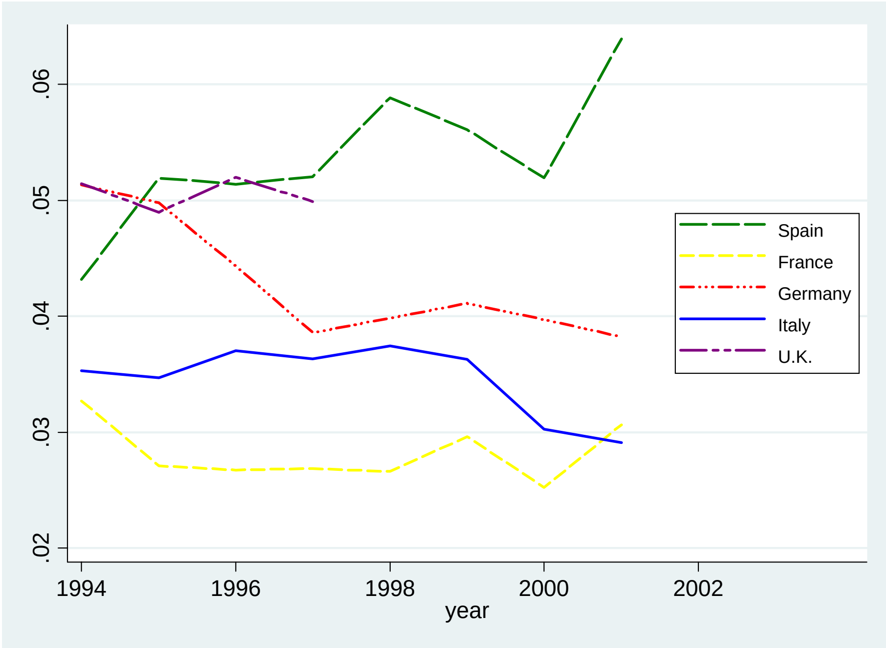

Figure 11: Welfare loss due to gender discrimination in the non-employed population (differences in returns using women's counterfactuals)