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Gender wage gap. A complete view from Italy

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Abstract

Wage discrimination has been widely investigated so that I try to contribute to this strand of the literature showing if there is evidence to exist in Italy for the period from 2000 to 2012 by using panel data from SHIW. Moreover, I focus the investigation on the informal labour market but I also do on the formal one. To get this, I perform Oaxaca-Blinder decomposition model. The main goal of these estimates is observing whether the results change when I include a variable to control non-random selection processes. In accordance with this, I obtain that gender wage gap is larger among formal workers when I control for this correction term than when I do not control for it and smaller among informal workers. Finally, I perform a robustness check to observe how this discrimination affects in each part of the informal workers distribution.

Keywords: wage discrimination, informal labour market, Italy, non-random selection

Index

1. Introduction and literature review

Shadow economy plays a role in the GDP of all the countries of the world although the size of this is different for each other. Recent estimates indicate that the undeclared sector represents a lower value for developed countries than for developing countries. In particular, Enste (2015) finds that german and italian shadow economies indicate 14.6% and 22.5% of GDP in the period 2003-2013, respectively meanwhile for countries such as Panama or Bolivia Schneider (2007) shows that it becomes almost 70% of GDP.

About the shadow economy behaviour, there is strong evidence to state that the size of it is counter-cyclical, that is, the size of the shadow economy as a ratio of GDP is bigger in bad bussiness cycles and is reduced in good ones (Elgin, 2012).

Regarding selections processes, there is evidence that the individuals follow non-random selection into jobs, meaning that formal workers are systematically different from informal workers in a way that affect their wages even after controlling for observable characteristics. Looking at European countries and the United States, Olivetti and Petrongolo (2008) point out that non-random selection explains why gender employment gaps are negatively correlated with gender wage gaps accross countries.

Since I consider that there is three possible statuses: unemployed, formal worker and informal one, I follow the Bourguignon, Fournier and Gurgand (2004) method by adding a correction term with I control for the non-random selection processes of staying either in a status or in another. According to the related literature, some investigators consider just two statuses and they follow the methodology proposed by Heckman (1973) (Tansel, 2001; Deininger et al., 2013) to control for selection.

In order to perform a study about this topic we need reliable data but this is not always possible because people who are interviewed could think that they have been investigated and they may not tell the truth in their answers. However, in the last years there have been some advances in this field by performing randomized experiments (Kleven et al., 2011) or by trying to solve the selection problem (Di Porto, 2011; Di Porto et al., 2013).

Regarding Italian shadow economy its size is around 22.5% of GDP as I mentioned above and is a country where there have been established some policies against it. An

example of these may be the Biagi reform with a focus on the objectives of the European Employment Strategy.

This reform was enacted by Legislative Decree No. 276/2003 and it aimed to raise employment levels, promote labour market access for disadvantaged groups and increase the number of workers in stable employment. It led to an increase in the level of this last goal but a proper assessment will only be posible in a longer time frame (Tiraboschi, 2005).

In this sense, Di Porto and Elia, 2013 use an identification strategy based on three amnesty laws and they suggest that all of them changed the shape of the undeclared sector in Italy causing a rapid emergence from this sector to the formal one. According to this statement, (Di Porto et al., 2013) performed an investigation to check if this effect was caused by these laws and they do not find a clear result.

A possible problem related with the ineffectivenss of labour policies is that there is evidence to state that there is no connection between formal and informal sectors what supports the failure to transform black employment into regular one over the last twenty years (Bovi, 2005).

Moreover, some investigators study the effect of the size of the undeclared sector on other labour market outcomes such as financial development (Capasso Jappelli, 2013) and they obtain that the local financial development is associated with a smaller size of the underground economy.

Focusing on how the undeclared sector structure is related with the level of education of workers, Cappariello and Zizza in 2010 conclude that the probability to end up working in this sector is higher for those who have performed fewer years of education. These results are based on the same data we use but for different years and they also suggest that the wages are slightly higher for individuals who performed the compulsory education with respect to those who did not in the informal sector.

If we refer to Italy's economy is worth mentioning the role of immigrants because it is a country characterized by receiving people from abroad in last recent decades. Moreover, this immigration has been chaotic because most of them are from individuals who run away from their origin countries.

Therefore, how they are integrated in the labour market is interesting and, in this sense, there is evidence to their jobs are full of irregular components, but difficult to divide from the functioning of the official economy and the host society (Ambrosini, 2001).

This paper is related to the literature on the dualistic view of the labour market and according to this view, the informal labour market is characterized by lower wages so that this paper presents some evidence to explain that the formal gender wage gap differs from the informal one.

Therefore, if we look at the female labour market history, we may observe that they have been rejected for several reasons until some decades ago, when they were able to enter the labour market after several fights. Despite having the possibility to get a job, there has always been evidence of wage discrimination as Hegewisch and Williams (2010) suggest.

In the last years governments from many countries have performed policies to reduce the discrimination although it is still persistent and pronounced between male and female in all the parts of the world (Hirsch, 2016).

In spite of this Oostendorp, R., 2009 studied the relationship between the economic development and the occupational gender wage gap in richer countries and he suggests that the gap tends to decrease with increasing economic development in these countries.

We may think that this discrimination is provoked by the different education level achieved by individuals because it is likely that women have not the same opportunities to study than men. However, Livanos and Núñez (2012) study the effect of the education level on the unexplained part of the wage gap, which is often related to discrimination, and they find that it is lower for graduates in Greece and UK.

In addition, Arhsad and Ghani (2015) also studied whether there exists the gap for the same education level and they suggest that in Malaysia male wages are much higher than female ones within each education group.

For Spain, de la Rica et al. (2008) also find that the gender wage gap is high and increases with the wage among highly educated workers while it is lower and decreases with wage among less educated workers.

We may also think that a way to reduce the gap is applying policies with the aim to increase the occupational integration because there is evidence that occupational segregation is strongly correlated with gender earnings inequality, as suggest Cotter and DeFiore, 1997.

If we look at Italy, Mussida and Picchio, 2014 used data for the last two decades and they find that the unconditional gender wage gap remained roughly constant over time, however, they also suggest that the component of the gap due to different rewards of similar characteristics deteriorated women's relative wage.

Moreover, these authors, by using microdata from Italy for the formal labour market, found that those women who had a lower education level are really penalized in their salaries (Mussida and Picchio, 2012).

Finally, focusing on papers which investigate gender wage gap in the undeclared sector we just find (Yahmed, 2016) where it is used data from Brazil and she finds that gender wage gap is higher in the informal labour market than in the formal one but she also argues that this may be provoked by the selection processes which determines why individuals choose either a sector or another. This is why she controls for endogenous selection into both sectors and we will try to do the same.

The remainder part is organized as follows. The Section 2 explains what data I use to estimate the model and how I obtained it and the Section 3 is about the empirical strategy I follow where I explain with detail why I perform each step. The next section shows the descriptive statistics and the fifth one presents the main results of the model. The last two sections are added to show some robustness checks and the conclusions.

2. Data collection

To perform the empirical analysis I use individual data from the Bank of Italy – Survey on Household Income and Wealth (SHIW). This dataset shows a highly detailed information from different perspectives by using some multipurpose surveys where we may observe distributional information and evidence on correlations such as family composition with economic behaviour. This is really important because it allows us to observe the effect through different subpopulations and to establish causality from a policy. The survey is carried out every two years and to the scope of this paper I consider the period 2000-2012. The target population includes individuals aged from 15 to 65 and amounts to 96299 observations. I restrict the sample to this range because these are the legal years to work according to italian laws. It also provides information on demographic characteristics, household composition, specifications related to the job, and standard labour market outcomes. To identify the experience of the individuals I consider the potential experience variable presented by substracting the age the individual is at contemporary moment and the age when he/she started to work. This way to calculate the potential experience presents some problems because it does not take into account those periods when the individual is not active in the labour market such as when he/she is unemployed. Regarding earnings, I compute them as the ratio between nominal earnings and the inflation rate using monthly values, because using salaries per hour may present some problems as I have to assume the number of weeks individuals work per month. I calculate wages this way to be able to compare them for all workers. Taking into account all of this, the definition I use to identify informal workers is considering those who have positive wages without receiving paid social security contributions throughout his working career. The latter information is obtained, as some investigators who use this survey (Di Porto Elia, 2013; Cappariello Zizza, 2010), with the following question: *Considering the employment history of. . . (name), did he/she ever pay, or his/her employer pay, the social security contributions even for a short period?* so that, if the individual gives a negative reply, along with a positive wage, there is evidence that he/she worked in the informal labour market (Di Porto, 2015). In addition, I generate another definition of informal worker by calculating a ratio between the same question I use above and the potential experience, although I just use this as robustness check. However, this definition may present some misreporting values since individuals may not say the truth about the earnings for fear of being

detected by the authorities, although I can exclude this possibility because the survey is anonimous. Moreover, to avoid problems about the tax calculation to obtain the net wages, I should use gross ones but it is not possible because they are not available and, therefore, it may lead to not too accurate results. Finally, due to labour market decisions and observed gender wage gaps differ accross the schooling distribution, I construct a regional unemployment rate for different education groups in order to identify the impact of lower labour demand even when controlling for regional dummies.

3. Estimation Strategy

As I mentioned across all the paper I replicate the model proposed in Yahmed (2016) with data from Italy, this will may be useful in two ways: the first one is upon the results she obtains in her investigation because if I get similar ones there is evidence that the model may be correctly specified and the second reason is that I may be able to contribute into this part of literature by performing some robustness checks and checking if this gap also exists when it is used different proxies of informal workers and using different subpopulations as I do in the final section of the paper.

In order to estimate the gender wage gap in the informal labor market and in the formal one I explain in this section the model I use where I first estimate the raw and adjusted wages by controlling for observable characteristics and then, I also control for selection into the different labour statuses.

3.1 The raw and adjusted wage gaps

This section shows some simple ways to obtain gender wage gap only controlling for observable characteristics. To do this I present how to calculate the raw wage gap and the adjusted wage one.

The first simple idea we could perform to obtain the raw wage gap in the different sectors from a simple equation:

$$\ln(w_{ij}) = \beta_0 + \alpha_j * F_{ij} + u_{ij} \quad (1)$$

where the dependent variable is the log wage and F is a dummy equal to one when indicates if the employee i is a woman and the sub-index j shows the sector where the individual belongs.

In this equation, I am interested in the coefficient we obtain (α_j) because it indicates the wage difference between male and female individuals[1]. However, this equation may present some important problems. One of them is that it is quite likely to obtain biased estimations due to the zero conditional mean assumption could not hold because I am not controlling for any individual characteristics.

On the other hand, to estimate the adjusted wage gap I use a version of wage gap decomposition model developed by Oaxaca (1976) and Blinder (1973) which separates the gap in two parts. The first one is due to group differences in the magnitudes of the independent variables of the referred outcome and into the second part does it for the effects of these variables.

To perform it, I estimate three equations, two separate wage equations for men and women and a pooled wage equation with gender dummies and an identification restriction such as Yahmed, 2016.

$$\ln(w_{ipj}) = \beta_{0pj} + \alpha_{pfj} * F_i + \alpha_{pmj} * M_i + X_i * \beta_{pj} + u_{ij} \quad (2.a)$$

$$\ln(w_{ifj}) = \beta_{0fj} + X_i * \beta_{fj} + u_{ifj} \quad (2.b)$$

$$\ln(w_{imj}) = \beta_{0mj} + X_i * \beta_{mj} + u_{imj} \quad (2.c)$$

where X is a set of variables to control for individual characteristics and it includes the number of years of education, age and its square, whether the individual was born in Italy, the experience and the experience square and indicators for the region where the person lives and for the sector of activity where he/she works.

Since this model follows a linear form I need the zero conditional mean assumption because the gap may be expressed as the difference in the linear prediction at the group-specific means of the regressors (Jann, 2008) because otherwise I would obtain biased results and it may be shown as

$$GAP = E(Y_A) - E(Y_{B)}) = E(X_A)'\beta_A - E(X_B)'\beta_B \quad (3)$$

[1] $E(ln(w_j)|female) - E(ln(w_j)|male) = \widehat{\alpha_j}$

because

$$E(Y_i) = E(X_i'\beta_i + \varepsilon_i) = E(X_i)'\beta_i + E(\varepsilon_i) = E(X_i)'\beta_i \quad (4)$$

In other terms, the decomposition allows for selection on unobservables as long as they are the same for both men and women and yield identical selection biases (Yahmed, 2016).

Despite of this, we may assume a weaker assumption called the ignorability one which implies that the distribution of the error term given X is the same for the two groups but it also may be problematic because the reasons why women and men choose working either into the formal sector or into the informal one may be different so that we suggest to adopt a model to be able to control for this through a selection function in the case of having these trouble.

Under the ignorability assumption, the total wage gap may be decomposed into three terms but we are just interested in the last two ones. These ones account for gender differences in the prices associated with given characteristics and it is expresses as

$$\overline{WG_J} = (\overline{X'_m} - \overline{X'_f})\widehat{\beta_{pJ}} + \overline{X'_f}(\widehat{\beta_{pJ}} - \widehat{\beta_{fJ}}) \quad (5)$$

where $\widehat{\beta_{pJ}}$ indicates the benchmark from the pooled sample using male and female observations

3.2 Treatment for selection into multiple employment statuses

In our model the individuals may be in three different statuses because they do not choose only between working or not working but also they have the possibility of working into the undeclared sector. This probability is different accross the individuals so that we provide a multinomial logit model with the goal to assign the probabilities to be in the different statuses for individuals regarding their characteristics and processes they follow. To do this I consider that the outcome may take one of the three different statuses: unemployed, employed in the formal labour market and employed in the informal labour market.

As I mentioned in the previous section the model I present controls for a selection equation which indicates the status in which the individual is conditional on the utility when it takes some values such as follows:

$$Y_i = j \; if \; V_{ij} > \max_{k \neq j}(V_{ik}) \quad (5)$$

In other words, I observe the status j for the individual i when its utility is the highest with respect to the other utilities.

Regarding assumptions I have to assume that the utility associated with each status is linear and their errors are independent and identically distributed (iid) so that I may estimate the probability of being in status j for individual i by using the multinomial logit model (McFadden, 1973).

$$P_{ij} = \Pr(Y_i = j) = \frac{\exp(X_i \lambda_i + Z_i \alpha_i)}{\sum_j^n \exp(Z_i \alpha_j)} \quad (6)$$

The full model I follow is

$$\ln(w_{ij}) = X_{1ij}\beta_{1j} + X_{2ij}\beta_{2j} + u_{ij}, \; if \; V_{ij} > \max_{k \neq j}(V_{ik}) \; for \; j = 2,3 \quad (7)$$

$$V_{ij} = X_{1i}\lambda_j + Z_i\alpha_j + \mu_{ij}, \; j = 1, \dots, 3 \qquad (8)$$

In this case the biased estimations are just obtained when both errors are correlated, in other words, when the unobserved characteristics from the selection process to be either in a status or in other one is correlated with the unobserved factors which affect to the individual's wage.

In the main equation (7), the independent variables represent variables which influence the wage in status j, in particular includes productive characteristics of the individual i such as the number of years of education achieved, his/her age and its square, whether the individual is italian, whether he/she lives in an urban area and to control for the status of the labour market among regions we add regional dummies and the unemployment rate sorted by education level and region what allows us to identify the impact of lower labour demand even when and regional dummies. On the other hand, the set of variables named includes some specifications that determine the wage of the

individual i but whose are just observable if he/she works: the time spent since the individal started to work (experience) and the experience squared and to control for the sector where the employee works I add indicators for the sectors of activity.

With respect to the selection equation (8), includes variables which determine the wage and influence the work status and is a set of characteristics that do not affect wages but are relevant to the work status identification such as the percentage of the individuals in the family who works and receives a salary or whether the individual is head of household.

Finally, to control for the selection process to stay either in a status or in another we adopt a particular term which is the following function h$(P_1, .., P_3)$ and it yields to the conditional mean of the error term. "Adopting Lee's Model (1983) approach, we assume that the joint distribution of u_j and a transformation of μ_j does not depend on the other μ_k for j$\neq k$"(Yahmed, 2016).

In addition, I also follow Dubin and McFadden (1984) who make less restrictive assumptions on the correlation between u_j and the $(\mu_k - \mu_j)$.

To consider the different points of view I estimate the correction term following the models proposed by Lee and Dubin and McFadden.

After including this new term in our Oaxaca-Blinder decomposition model we obtain the following results:

$$\overline{\ln W_{mj}} - \overline{lnW_{fj}} = (\overline{X'_m} - \overline{X'_f})\widehat{\beta_{pj}} + \overline{X'_m}(\widehat{\beta_{mj}} - \widehat{\beta_{pj}}) + \overline{X'_f}(\widehat{\beta_{pj}} - \widehat{\beta_{fj}}) + \theta_{mj}h_{mj}(P_1, .., P_3) - \theta_{fj}h_{fj}(P_1, .., P_3) \quad (9)$$

$$\overline{WG_{sj}} = (\overline{X'_m} - \overline{X'_f})\widehat{\beta_{pj}} + \overline{X'_f}(\widehat{\beta_{pj}} - \widehat{\beta_{fj}}) \quad (10)$$

The first equation shows the total decomposition when the additional term is added to the model and it captures the average in difference selection bias. In addition, the interpretation of this term has been treated on different ways in the literature of wage decompositions but I follow Yun (2007) who advocates treating selection as a separate term. Therefore, the selection term provides a measure of the difference between the observed wage gap and the gap in wage offers.

On the other hand, the second one presents the wage gap between male and female individuals and it is not equal to that showed in equation (3). The main difference with that one is that (10) estimate consistently the coefficients following the treatment for selection.

3.3 Identification

In this section I explain some exclusion restrictions needed to identify the effect of selection and vanish the selection bias from the wage estimates without relying on the functional forms. These restrictions mean that there are some variables which affect wages only through the status where they stay. Since I am performing a replication from Yahmed (2016) I try to use the same variables as long as they are available.

Therefore, the excluded variables I chose are the following. The first one is whether the individual is head of household, because it may influence to stay either in a status or in another due to the fact his/her income is the main one.

The second variable I use is the number of people compose the household, because I think that, if this value is higher, the individual will consider working in the formal sector to give to his/her family more security. In this sense, I also use the share of individuals who receives income from working.

Finally, I consider two more variables where the first one represents the individual's civil status, because there is evidence that women may be conditionated to choose the sector to work depending on whether they are married. The last variable I include is the region where the individual was born because it may represent a strong characteristic to be either a formal worker or an informal one.

4. Descriptive statistics

In this section I show some different specifications of the individuals to defend the model I estimate in the final part of the paper. I present these specifications through the following tables and distribution graphs.

Table 1 shows some main variables from own characteristics to job related ones. In first place, we may observe that in both sectors the mean of years of schooling are higher for women than for men, this may be explained by the fact of those women who want to work are high-skill workers. Moreover, these means are lower for the informal labour market such as Addabbo and Favaro in 2011 suggested.

Regarding the mean of age in each sector we may observe that it is much higher for the formal sector than for the informal one where this value is around thirty four years. A plausible explanation of this may be that as people get older give preference the stability received from the social security. The variable which represents whether the individual is the head of household takes higher values for men than for women in both sectors. This may agree with cultural believes about it has to be the man who brings income to home meanwhile the woman cares about the children and the house.

If we focus on Italian individuals we may observe that there are more ones in the formal labor market than in the informal ones. A job related characteristic we may looking at is experience average for each sector and, we may observe that the value shows a higher value (around 21 years) for the formal sector than for the informal one (around 12 years).

According to the composition of household we may observe to the number of people are composed and the share of household member who are working and the values they take are really similar for both sectors.

Finally, I focus on the public sector because it does not have to have informal labour market but the question I am using may lead to mistake because it does not include companies in which the government is a stakeholder, such as the postal service and the national railways. Regarding the data we may observe that it is higher the share of women working in this sector than the share of men. I also present whether the individual works in his/her main job and we may observe that almost all the individuals interviewed do.

Table 1

	FORMAL				INFORMAL			
Variables	Men	Columna2	Women	Columna1	Men	Columna3	Women5	Columna4
Years of schooling	4,2041	(1,445537)	4,6466	(1,457972)	3,675	(1,39856)	4,327	(1,517042)
Age	4,1788	(1,097993)	4,1569	(1,025952)	33,632	(11,33673)	35,006	(11,54569)
Head of household	0,7626	(0,4254857)	0,3550	(0,4785411)	0,581	(0,4936601)	0,311	(0,4631467)
Italian nationality	0,5122	(0,4998626)	0,5362	(0,4987014)	0,456	(0,4983481)	0,498	(0,5004024)
Experience	2,1944	(1,179359)	20,0354	(11,12954)	13,791	(11,7172)	11,611	(11,12225)
Number of people	3,3686	(1,177708)	3,1451	(1,177455)	3,677	(1,422259)	3,364	(1,344346)
Share of household members working	0,6550	(0,2672368)	0,7522	(0,2245641)	0,621	(0,2657489)	0,746	(0,2305557)
Civil status	1,3833	(0,5748167)	1,5283	(0,7608407)	1,635	(0,534897)	1,811	(0,723365)
Public sector	0,2298	(0,4207182)	0,3425	(0,4745842)	0,109	(0,3117414)	0,157	(0,3643865)
Main job	0,9950	(0,0707806)	0,9961	(0,062127)	0,995	(0,067002)	0,982	(0,1323286)

Source:.Author's calculation based on the SHIW 2000-2012, Italy. Standard deviations in parenthesis. Values represent the mean of each variable for each sector and gender.

Table 2 shows the share of individuals who stay in each status and in each sector for the different educational levels.

We find the biggest gender difference among workers for the lower secondary education level while the smallest one is in the tertiary education level among unemployed individuals.

Finally, we may observe that women perform more educational years than men among workers and considering unemployed individuals are women who achieve less education levels. All this coincides with the evidence I found into the related literature.

Table 2

	All		Unemployed		Formal		Informal	
	Men	Women	Men	Women	Men	Women	Men	Women
Primary education	11.58	16.93	17.23	24.39	7.40	4.99	14.64	8.09
Lower secondary education	38.06	32.97	42.07	38.46	35.68	23.84	46.40	31.72
Upper and post secondary education	40.06	38.62	34.02	30.92	44.72	51.86	32.09	45.15
Tertiary education	10.31	11.48	6.68	6.23	12.20	19.32	6.87	15.05

Source: Author's calculation based on the SHIW 2000-2012, Italy. It shows the share of individuals who stay in each status and in each sector for the different educational levels.

Table 3[2] presents the regional unemployment rate by gender and different educational levels. We may observe that this rate is much higher for female individuals in all education groups. Despite of this, the value gets lower for the higher educational levels. Therefore, the biggest difference occurs in primary education level. In order to identify the impact of lower labour demand I include an index which represents the regional unemployment rate for educational levels as control variables.

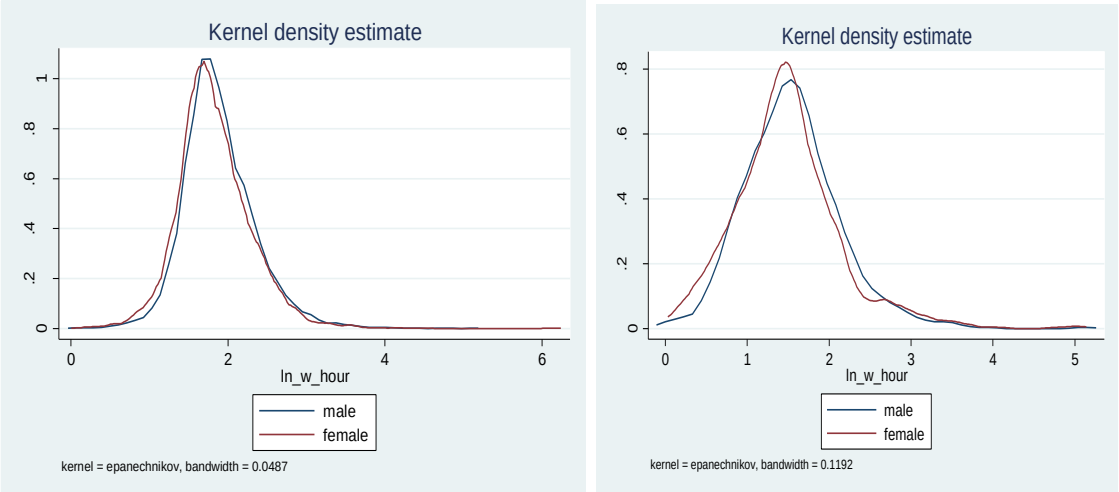
To complete the data description I present some distributions to observe how the wages are distributed across the sample.

We may observe that, among formal workers, the wage distribution is really similar although is a little bit fatter on the left side for women. If we look at the informal sector we may appreciate that women wage distribution is shifted farther to the left showing us that there exists a distributional gender wage gap.

Moreover, this fact occurs at all educational levels in both sectors since we may observe. In the next sections I show whether this gap is different between the sectors and whether it occurs even when controlling for some different variables.

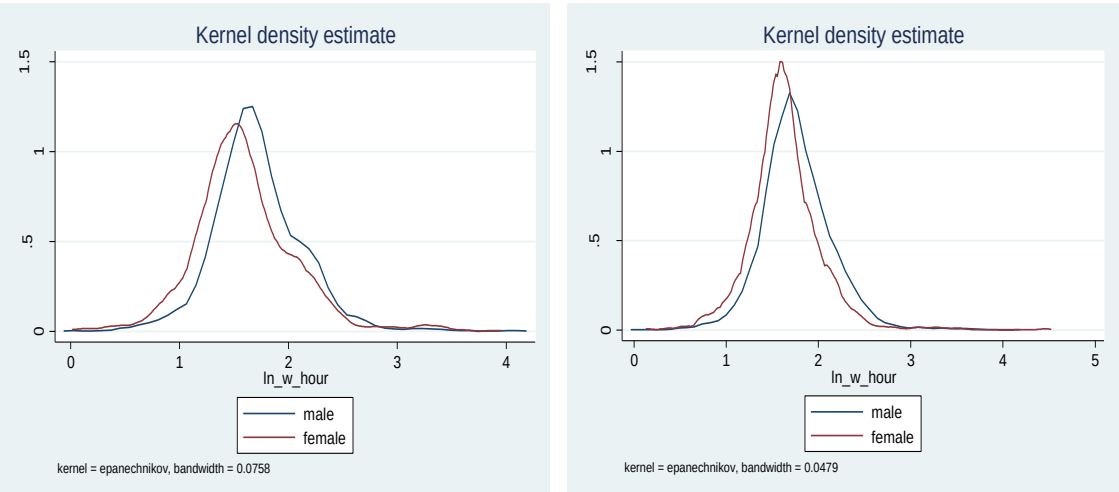
[2] Table 3 is showed in the Appendix

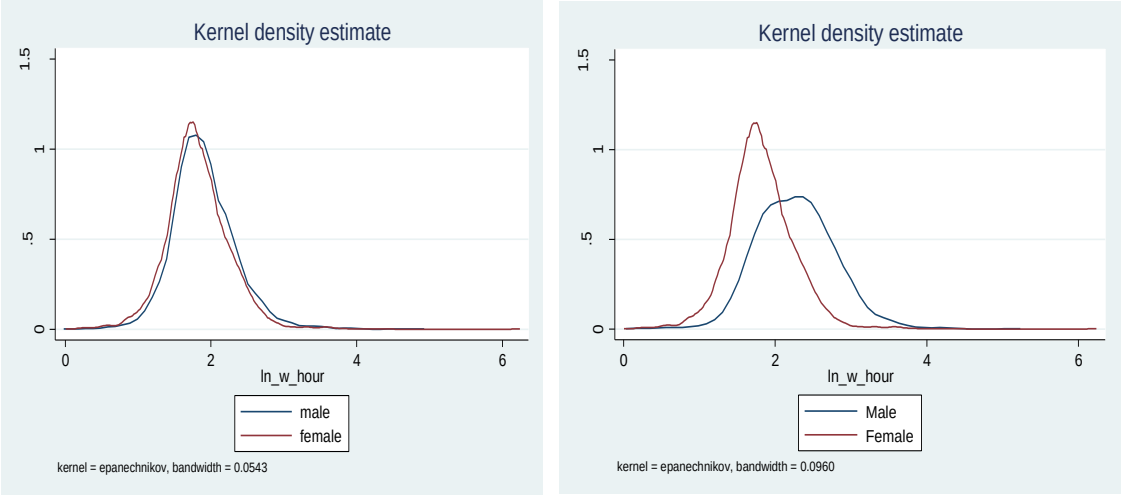
Figure 1



Source: Author's calculation based on the SHIW 2000-2012, Italy. It shows wage distribution for each sector and gender. The left-side figure represents the formal sector and the right-side one, the informal sector.

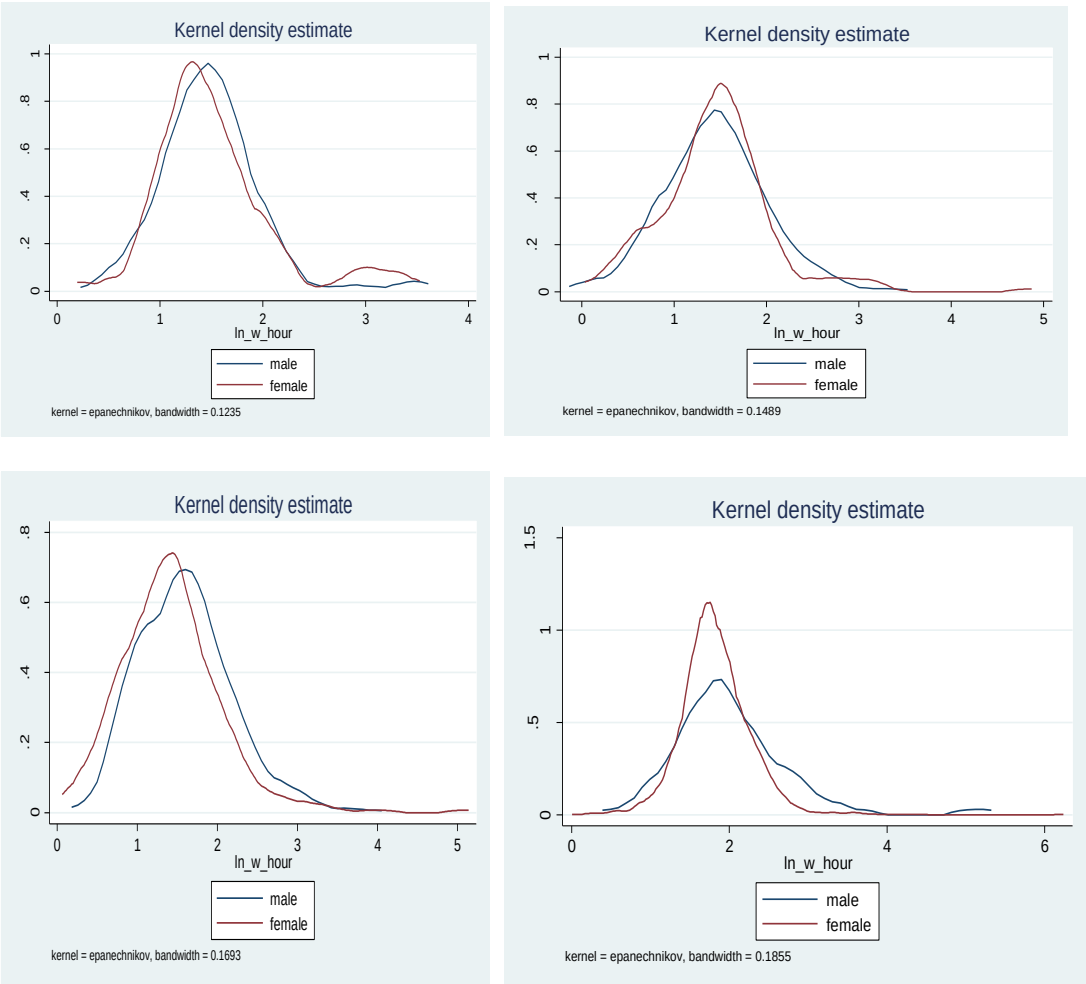
Figure 2





Source: Author's calculation based on the SHIW 2000-2012, Italy. It shows wage distribution for each gender among formal workers by different educational level. The images are organized as Primary education, Lower secondary education, Upper and post secondary education and Tertiary education, respectively.

Figure 3



Source: Author's calculation based on the SHIW 2000-2012, Italy. It shows wage distribution for each gender among informal workers by different educational level. The images are

organized as Primary education, Lower secondary education, Upper and post secondary education and Tertiary education, respectively.

5. Results

In this section I show the estimations of the model presented in the "Estimation Strategy" section.

I start the empirical analysis by commenting the multinomial logit estimates for each sector and gender.

In first place, if we look at the formal labour market coefficients for men we may appreciate that the probability of being in this status is different for the individuals depending on their characteristics. This is clear because all the coefficients are significant at all levels.

Moreover, all the signs make sense. For instance, we expect that if the individual is the head of household, the probability to work in the formal sector increases because it guarantees some stability.

In second place, if we focus on the informal labour market, we may observe that we obtain almost the same results as in the formal sector. In this sense, it is worth mentioning the fact of the educational level obtained has opposite effects in both sectors, showing a negative effect when this level increases.

Regarding women's results, we may observe that in the formal labour market the variables included in the equation are significant and the signs are the expected.

Comparing them with the informal estimates we may observe that the results are the same, even the educational level sign.

Since I mention above, the first equation I estimate the raw gender wage gap with no control variables for the formal and informal sector. In this equations, the coefficient obtained represents the gap.

If we look at Table 6 the coefficients of the raw gender wage gap estimation show that there is evidence of a negative gender wage difference for women in both sectors and it is significant from 1% level. Moreover, among formal workers the gender wage gap arises to 23.5% while among informal workers it is around 26.6%.

Table 4

Formal status	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Age	0,60117	0,0079375	75,74	0	0,5856163	0,6167308
Ages square	-0,00798	0,0000956	-83,43	0	-0,0081642	-0,0077894
Level of education	0,16798	0,0103494	16,23	0	0,1476933	0,1882623
Italian	0,15770	0,0296269	5,32	0	0,0996321	0,2157675
Head of household	2,51256	0,0418568	60,03	0	2,430517	2,5945920
Number of components	0,39458	0,0159806	24,69	0	0,3632588	0,4259014
Share of household men	2,98332	0,0712471	41,87	0	2.843.675	3.122.959
Civil status	-0,63015	0,0332102	-18,97	0	-0,6952397	-0,5650581
Birth municipality	-0,13705	0,0175906	-7,79	0	-0,1715248	-0,1025711
_cons	-1,32722	0,2101364	-63,16	0	-1.368.409	-1.286.037

Notes: Multinomial logit estimates for the formal sector based on the SHIW for 2000-2012, Italy. All the coefficients are statiscally significant at 0%, 5% and 10%.

Table 5

Informal status	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Age	0,40892	0,0211	19,41	0	0,3676263	0,4502194
Ages square	-0,00631	0,0003	-23,11	0	-0,0068475	-0,0057767
Level of education	-0,10228	0,0302	-3,39	0,001	-0,1614114	-0,0431536
Italian	0,04404	0,0761	0,58	0,563	-0,1050993	0,1931708
Head of household	2,48686	0,1021	24,35	0	2,286683	2,687037
Number of components	0,48028	0,0363	13,24	0	0,4091786	0,5513811
Share of household members working	3,25094	0,1782	18,24	0	2.901.665	360.022
Civil status	-0,36761	0,0945	-3,89	0	-0,5527653	-0,1824499
Birth municipality	0,83811	0,0579	14,46	0	0,7245482	0,9516813
_cons	-1,38666	0,5202	-26,66	0	-1,488616	-1,284694

Notes: Multinomial logit estimates for the formal sector based on the SHIW for 2000-2012, Italy. All the coefficients are statiscally significant at 1%, 5% and 10% except the Italian nationality. This is significant just at 10% level.

Table 6

ln_w_month	(1)		(2)
fem	-0,2358756***		-0,2669935***
	(0,0047615)		(0,0305402)
_const	6,935064		6,541
	(0,0029503)		(0,0184647)

*Notes: OLS estimates. Column (1) shows the results for the formal labour market and (2) presents those for the informal one. Robust standard errors are in parenthesis. *** significant at 1%. Variable "fem" refers to female individuals.*

The coefficients of the raw gender estimation show that there is evidence of a negative gender wage difference for women in both sectors and it is significant from 1% level. Moreover, among formal workers the gender wage gap arises to 23.5% while among informal workers it is around 26.6%.

However, this coefficient may be biased for the reasons I mentioned above.

Table 8 shows the results obtained from following the Oaxaca-Blinder decomposition model controlling for observable characteristics. From this, we may observe that wage gap due to differences by gender in productive characteristics among formal workers shows evidence that the difference should be positive for women, but the unexplained one becomes 26.4%. This value is even higher than the result presented in the first equation and it may be explained by the fact of women are positive self-selected.

Regarding the informal sector, there is evidence to the total gender wage gap arises to 32.62% and most of it is from the unexplained part. This coincides with the same reasoning from above so that I present the same estimates but including the correction term to control for non-random selection processes. If selection into a status of work is indeed non-random, observed wages either overstate or understate wage offers.

These estimates are showed in the rows from (3) to (6). The different estimates include the correction term following the two approaches explained above. Moreover, the term's estimates are obtained after setting a hundred of repetitions.

Table 7

		Coef.	Robust SE	z	P>z	[95% Conf.	Interval]
	difference	0,2410407***	0,0086466	27,88	0	0,2240937	0,2579877
(1)	explained	-0,0235972***	0,0061078	-3,86	0	-0,0355683	-0,0116261
	unexplained	0,2646379***	0,0079006	33,5	0	0,249153	0,2801228
	difference	0,3262214***	0,0574351	5,68	0	0,2136507	0,4387921
(2)	explained	0,0721032	0,0511183	1,41	0,158	-0,0280869	0,1722932
	unexplained	0,2541182***	0,0677344	3,75	0	0,1213612	0,3868753
	difference	0,2257217***	0,0089585	25,2	0	0,2081633	0,2432801
(3)	explained	-0,0062772	0,0066391	-0,95	0,344	-0,0192895	0,0067351
	unexplained	0,2319989***	0,0082761	28,03	0	0,215778	0,2482198
	difference	0,335007***	0,0638962	5,24	0	0,2097727	0,4602414
(4)	explained	0,1161096*	0,060777	1,91	0,056	-0,0030111	0,2352303
	unexplained	0,2188974***	0,0759535	2,88	0,004	0,0700312	0,3677636
	difference	0,2257217***	0,0089585	25,2	0	0,2081633	0,2432801
(5)	explained	-0,0169073**	0,0065442	-2,58	0,01	-0,0297336	-0,004081
	unexplained	0,242629***	0,0082957	29,25	0	0,2263697	0,2588883
	difference	0,335007***	0,0638959	5,24	0	0,2097733	0,4602408
(6)	explained	0,1200233**	0,0610742	1,97	0,049	0,00032	0,2397266
	unexplained	0,2149837***	0,076454	2,81	0,005	0,0651366	0,3648308

*Notes: Oaxaca-Blinder decomposition estimates. Panel (1) and (2) show the results controlling for observable characteristics for both sectors. Panel (3) and (4) present the estimation controlling for non-random selection following Lee's approach. Panel (5) and (6) the same than (3) and (4) but following Dubin and McFadden's model. Robust standard errors are in parenthesis. *** significant at 1%. ** significant at 5%. * significant at 10%. These estimates are based on SHIW data for 2000-2012. Control variables used are educational level, age, age square, potential experience, potential experience square, Italian nationality and regional unemployment rate. Selection equation: controlling for the same previous variables and head of household, number of components in the household, share of household members working, civil status and birth municipality.*

As expected, among formal workers there is evidence of a decrease in the gap which supports the idea that women are positively selected. This leads to larger results, therefore, there is evidence that gender wage gap is overestimated. This may be explained by the fact of employers offer lower wages to women because they have a higher quit probability so that they expect to face higher labour costs.

However, among informal workers I can appreciate that there is evidence that total gap is also larger than when controlling for observable characteristics. Moreover, the unexplained part shows a decrease in both cases. This reduction comes from the inclusion of the correction term which captures the non-random selection processes.

In addition, this is related with the idea mentioned above that women are positively selected which means that only those who are more prepared work. Therefore, these results are consistently estimated and support the evidence of wage discrimination against women.

6. Robustness checks

To complete the investigation and checking whether the results obtained are reliable I perform some estimations by considering another definition of informal workers. I use a ratio between the same variable I use in the model and the potential experience and take into account the percentiles of it. I apply this quantile decomposition to analyse the changes of the gender wage gap at different points of the wage distribution.

I estimate the gender wage gap by using the Oaxaca and Blinder decomposition model controlling for observable characteristics as I do in the first part of the previous section.

The table shows the results obtained and they present evidence that the gap is higher as workers perform a higher percentage of their worklife in the informal sector. Moreover, we may observe that this discrimination decreases when we look more to the right of the distribution. In other words, when workers have been fewer years in this sector, the gap is smaller.

Finally, we may observe that the unexplained part represents most of this difference. In addition, this wage gap due to differences in returns for the same characteristics presents smaller values when the observed part of the distribution is closer to the bottom.

Table 8

		Coef.	Robust SE	z	P>z	[95% Conf.	Interval]
	difference	.3308049	.0863322	3.83	0.000	.1615969	.5000129
p05	explained	-.106175	.059006	-1.80	0.072	-.2218246	.0094745
	unexplained	.43698	.0792307	5.52	0.000	.2816907	.5922693
	difference	.3197186	.0368393	8.68	0.000	.2475149	.3919223
p15	explained	-.0611753	.0229195	-2.67	0.008	-.1060968	-.0162539
	unexplained	.3808939	.0355006	10.73	0.000	.311314	.4504739
	difference	.2959545	.0245648	12.05	0.000	.2478084	.3441006
p25	explained	-.0522043	.015873	-3.29	0.001	-.0833148	-.0210938
	unexplained	.3481588	.0240867	14.45	0.000	.3009497	.3953679
	difference	.292619	.0195673	14.95	0.000	.2542677	.3309703
p35	explained	-.0494643	.0130548	-3.79	0.000	-.0750514	-.0238773
	unexplained	.3420833	.0186921	18.30	0.000	.3054476	.3787191
	difference	.2679861	.0164273	16.31	0.000	.2357891	.3001831
p45	explained	-.0508064	.0114458	-4.44	0.000	-.0732397	-.0283731
	unexplained	.3187925	.0158132	20.16	0.000	.2877992	.3497858

*Notes: Oaxaca-Blinder decomposition estimates.. Robust standard errors are in parenthesis. *** significant at 1%. ** significant at 5%. * significant at 10%. These estimates are based on SHIW data for 2000-2012. Control variables used are educational level, age, age square, potential experience, potential experience square, Italian nationality and regional unemployment rate. Selection equation: controlling for the same previous variables and head of household, number of components in the household, share of household members working, civil status and birth municipality.*

7. Conclusions

After presenting all the results I can conclude that there is evidence of wage discrimination in the formal and informal labour market during the period from 2000-2012 in Italy.

Despite of the existence of it, I obtain that this gap is smaller when I control for non-random selection processes following different models proposed by Lee, Dubin and McFadden. As I mention above, it supports the idea of positive selection and presents evidence of overestimating gender wage gap when just controlling for observable characteristics.

In addition, this gap is almost completely unexplained by observed characteristics, applying SHIW data for the mentioned period. I also provide evidence across the distribution and it showed the discrimination is larger among workers who spent most of their worklife in the undeclared sector.

If I compare the results obtained in this paper with Yahmed's ones I may observe that they are different. Yahmed (2016) present a qualitatively different gender wage gap from Brazil than the one I show here in formal and informal sectors (5% and 13% vs 22.5% and 33.5%). These differences may be explained by the different laws are in each country and how they influence wage offers by gender. Another interesting explanation may come from the different development levels the countries have.

Moreover, if I revise gender wage gap literature I find that some investigations suggest a smaller gap (Piazzalunga and Di Tommaso, 2015; Mussida and Picchio, 2014). However, when they control for non-random selection, I think that the different results are due to the fact of they just consider two statuses and perform the model proposed by Heckman (1974).

In this sense, it would be interesting perform some estimations by using subpopulations to check whether the size of the discrimination. These subpopulations could be either immigrant individuals or classifying by civil status because some studies have found that female individuals have different incentives to invest in human capital. Another interesting idea would be considering a country where there exists the same laws for men and women when they have children. By using this, I think it is able to find whether this policy gets to reduce wage discrimination.

Finally, I perform the investigation by considering the monthly wages but I checked that there is evidence that considering hourly ones the results are qualitatively similar.

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9. Appendix

Table 3

Unemployment rate	Primary education	Lower secondary education	Upper and post secondary education	Tertiary education	Total
Male	0,3658522	0,3775373	0,3684616	0,3676608	0,3738414
Female	0,6277226	0,6013935	0,5791982	0,5715309	0,5938517

Source: Author's calculation based on the SHIW 2000-2012, Italy. The regional unemployment rate by gender and educational level