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THE QUESTION OF THE GENDER PAY GAP IN ITALY

A STUDY ON THE DATA OF THE BANK OF ITALY

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La tesi di Laurea Magistrale che mi accingo a presentare conclude la mia carriera universitaria e scolastica dopo quasi vent'anni dal suo inizio. Vorrei dunque dedicare questo lavoro alla mia famiglia, che è sempre stata presente nel sostenere i miei momenti di difficoltà e nel festeggiare i momenti di gioia.

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Chapter 1
Introduction

1.1 The question of the Gender Pay Gap

Every day, around the Globe, women suffer the consequences of gender discrimination. The phenomenon extends to a number of circumstances: there is evidence of gender discrimination in education, labor force participation and remuneration, participation to political life and decision making at high level, but women suffer to greater extent also of female infanticide and sex-selective abortion, domestic violence, child marriage, objectification and so on. This analysis will focus on the economic side of gender discrimination, and specifically on the estimation of the discriminatory part of the Gender Pay Gap.

Within the labor market, *discrimination exists when workers with the same productive capacities are treated differently on the basis of the demographic group to which they belong*. Ever since the scientific literature has started to develop models on discrimination in the labor market, a number of scholars tried to measure its impact on the wage differentials of different groups of people.

Initially, the focus was on discrimination against ethnic groups (typically against Black in the United States). But soon, the same techniques extended to the study of discrimination by age, physical or mental disability, sexual orientation, immigrant status, and last but not least, gender.

In no country in the World women's wage equals that of men. This happens everywhere, no matter how economically developed the country is, or how much the labor market is regulated. Women earn less if we measure salaries on an hourly, weekly or even annual base, but telling how much of this difference is due to discrimination is a rather difficult task.

In this work I will try to analyze the question of gender pay gaps in Italy, and isolate the discriminatory component of the differential. Following the definition of discrimination provided above, we can immediately understand that the main problem of measuring the size of the wage gap due to discrimination is that of controlling for the productive capacities of the two groups (women and men). We can tell how much female employees are discriminated (with respect to male) only once we are sure we are comparing individuals who differ *solely* by their gender.

Three things attracted my attention towards this topic and pushed me to go in details into this kind of analysis. First, *the phenomenon is present worldwide and it interests an incredibly high share of the global population*: women in dependent employment are remunerated less than their male counterparts in every country in the World. To this, we should add the indirect effects that wage gaps have on employment decisions, participation choices etc. which interest an even higher share of the total female population. Second, *inequality in pay has disruptive consequences on women's psyche, working lives, pensions and – in turn – on the overall economic development of a country.* Hence, tackling gender pay gaps would have positive consequences on all these dimensions and improve sensibly the life quality of individuals and the surrounding community. Finally, *the gender pay gap can be statistically measured and its development can be tracked over time*, hence it is possible to check whether each country is progressing in closing the differential, and which is the impact of external shocks on the size of the gap.

1.2 Main findings

We first provide an overview of the trend of the unadjusted gender pay gap in Italy during the last few years, compared with that of other European countries. The unadjusted gap is obtained by computing the difference between the mean wage of men and women. Since it does not take into account gender differences in the endowment of productive characteristics, it cannot be interpreted as a measure of wage discrimination. We will then apply the renowned Oaxaca-Blinder decomposition with Heckman correction for the choice of labor market participation to Italian data relative to 2012 (Survey of Household Income and Wealth of the Bank of Italy) in order to extract the discriminatory part of the differential (adjusted wage gap). We find that despite the raw gap is among the lowest in Europe (5,1% in our data), the adjustment leads to sensibly different results: discrimination creates a gender wage differential between 8,4 and 9,4%, depending on the controls employed to estimate wages.

1.3 Structure of the dissertation

The dissertation will be structured as follows:

- *Chapter 2* starts with a general overview of the Gender Gap around the World. Eventually, we will present the current situation of Gender Pay Gap (as a “sub-set” of the Gender Gap) in Italy, in comparison with other European countries. Attention will be devoted to the analysis of other phenomena strictly related to wage differentials, such as part-time employment, participation trends etc.

- *Chapter 3* provides a description of the previous literature dealing with the question of wage gaps in Italy. In particular, a detailed analysis of the econometric techniques employed has been included.
- *Chapter 4* presents the data employed in my analysis and the various controls available for the estimation of the wage and participation equations.
- *Chapter 5* describes and criticized the results.
- *Chapter 6* concludes the dissertation.

Chapter 2
An economic analysis of the Gender Pay Gap and its determinants

In this chapter we will present the current situation of the Gender Gap around the Globe and we will briefly explain how the concept of Gender Gap can be conceived under many dimensions. Eventually, we will focus on the Gender Pay Gap (GPG) in Italy, making numerous references and comparisons with the European framework. We will devote particular attention to those phenomena that are strictly connected to the GPG and are likely to affect its size: labor participation trends, gender segregation, part-time employment and cultural context.

2.1 Gender Gap around the World

The World Economic Forum (WEF) has recently issued its annual report on Gender Gap around the Globe (World Economic Forum, 2013). Since 2006 the

Foundation develops the Global Gender Gap Index (GGGI), which is a quantitative indicator aimed at capturing the magnitude and scope of gender-based disparities and tracking their progress over time. The concept of Gender Gap can be extended to a number of dimensions, but the WEF constructs its index by focusing only on four contexts in which gender disparities may arise: the “Economic Participation and Opportunity”, “Political Empowerment”, “Educational Attainment” and “Health and Survival”. The indicator controls for gender gaps in access to education, literacy rates, access to parliamentary and minister-level positions, life expectancy and – particularly relevant for the purpose of this work – three labor-related gender differentials: in participation, in remuneration and in advancement opportunities.

The WEF estimates that in 2013 the World[1] had closed as much as 96% of the health gap between sexes and 93% of the differential in educational attainments, with 33 nations having completely shut the former, and 25 the latter. This is a remarkable result that gives us hope that gender equality is indeed an achievable goal. Wide educational and health disparities seem to be still present only in some African and Middle-Eastern countries, while in the rest of the World women have almost caught up with men[2]. However, the outcome regarding the other two pillars is not as good. The gap remains wide: only 60% of the differential in economic participation has been closed, while for political empowerment the figure is only 21%.

On top of the rank there are the Northern European countries (Iceland first, and then Finland, Norway, Sweden and Denmark, all occupying top10 positions). The index is constructed by grading countries according to women's performance

1. Average of the 136 countries included in the survey, covering over 90% of the global population.
2. In some advanced economies a stable trend has arisen in the last decades: more girls than boys enroll in University and they are generally less likely to drop off.

relative to men's, rather than their performance overall. Hence nations with high living standards are not necessarily advantaged (Philippines is fifth worldwide). Despite this, all the Nordics made it to the top. An accurate mix of economic and social policies made it possible: paternity leaves, tax incentives, post-maternity re-entry programmes etc. resulted in more shared participation in child-care, high female employment, better work-life balance and in some cases, a boost to the birth rate. Minimum quotas on female participation in companies boards and political parties were introduced many years ago, and in Denmark have already been abandoned as no further stimulus is required.

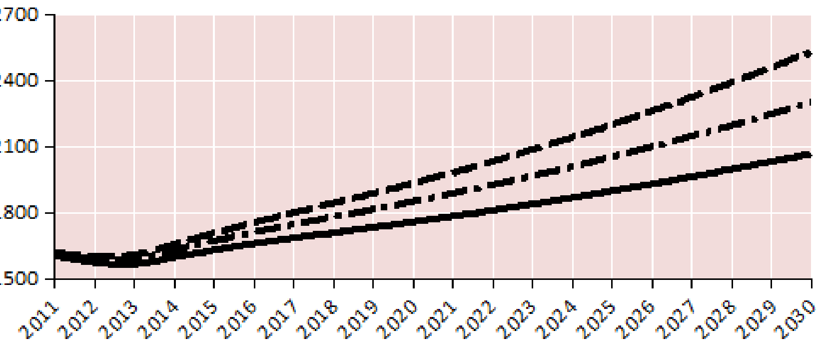
These countries serve as examples for other nations seeking gender equality. The majority of the countries in analysis progressed on closing gender gap since the launch of the WEF report in 2006. Most of the advancement has been done in the political and economic tranches, being them the most backward still now. Instead, education and health seem to be at a standstill.

The index continues to track the negative correlation between a country's competitiveness and the size of its gender gap[3]. However, when we look at the causal relation between the two phenomena, narrowing differentials are likely to be a *cause* rather than an *effect* of development: long term competitiveness depends on human talent, and women account for a half of a country's potential talent base. By offering equal opportunities, responsibilities and rights to women, a country can significantly enhance its economic potential and guarantee a balanced and thriving development. For example, Daly (2007) reckons that equal employment rates for women and men would result in a 13% higher GDP in the Eurozone[4], in addition to alleviating the problem of aging working population.

3. The concept of competitiveness refers here to another indicator developed by the World Economic Forum: the Global Competitiveness Index (GCI). The countries having high GCI tend also to have high GGGI, and vice-versa.
4. This under the debatable assumption of leaving productivity and average hours worked unchanged.

The OECD (2012) envisage that every nation would sensibly improve its GDP projections for the next 15 years, if the participation gap was reduced (even by only 50%). And Italy, in particular, would benefit the most among OECD countries (see Figure 2.1).

***Figure 2.1** – Italy's GDP projections*



Source: OECD (2012)
Note: proceeding from the lowest line to the top one, the first is the trend with no change in employment gap, the second is the forecast with 50% reduction, and the last is with complete convergence.

Gender disparities can arise in a number of contexts and ways. In its report, the WEF focuses on *some* aspects (namely, the four pillars I've already mentioned) and develops *some* concise indicators that may prove particularly user-friendly for international comparison. But the picture is more entangled than that. Firstly, all these dimensions are deeply interconnected. For example we might expect the educational gap to be closely linked to (and have strong repercussions on) participation gaps and wage differentials. But then one question spontaneously arises: why is it that men and women receive today more or less the same education, while disparities in the labor market are still far from being filled? Secondly, the report doesn't go in details studying the different countries' frameworks. The cultural and institutional context where gaps arise can explain much about differentials and, most importantly, about the discriminatory part of differentials (for example, part-time employment is more common among women and this can partially justify why wage gaps are so wide in some countries when annual salaries are compared).

In this work we will only focus on *one country* – Italy – and on *one dimension of gender gap*: the Gender Pay Gap. However, we will take into consideration a number of factors that can affect the size of the wage gap: gender differences in labor-force participation, educational attainments, occupation and industry-level segregation, and last but not least the Italian cultural and social framework.

2.2 Gender Gap and hourly Gender Pay Gap in Italy

In its study, the WEF places Italy in the 71st position out of 136 nations considered. According to the statistics, Italy has closed 69% of its overall Gender Gap. The result is all but thrilling, especially considering that most of the other high-income economies around the world do better than that. Italy is 97th for Economic Participation and Opportunity (60% of the gap closed), 65th in Educational attainment (99%), 72nd in Health and Survival (97%) and 44th in Political Empowerment (19%).

The results on education and health are not the most alarming. The country is not among the best in the world, but the gaps are almost entirely closed. In education, boys outperform girls only in primary school enrollment, but the gap is reversed for tertiary education. The literacy rate is almost 100% for both men and women, and there is no sensible differences between the two. The sex ratio at birth is almost 1:1, and women tend to have a longer life expectancy than men.

As for political empowerment, Italy does relatively better than many others, although the gap is still wide. Female presence in parliament doesn't go much beyond 30%, but is considered high if compared with the world average. Moreover, Italy has never had a woman Head of the State, but this is common to many other nations, so it doesn't affect much the relative performance. “Europe and Central Asia” is the region that currently has the best results in female participation in politics. However, since 2010 the index relative to this pillar has stalled, while other regions (like “Asia and the Pacific”) are witnessing substantial and continuous improvements. Sensible advancements on this side are needed, not only by Italy but by most of the countries included in the WEF analysis. The gap is still wide open, and the way to achieve equality is long.

Most of Italy's problems arise in the Economic Participation and Opportunity component of the index. Italy is recorded 124th for wage equality for similar work (an information that the WEF collects with an internal survey). The gap in annual earnings is huge (on average. women earn slightly more than half of what men do), and the female labor-force participation is not even 70% of that of men. Adding all these things up, the resulting overall performance is rather disappointing.

Looking at other sources this might sound surprising: in the 2010 Final Report of Gender Wage Gap by the Council of the European Union (Council of EU, 2010), Italy is recorded as the European country with *the lowest gender wage gap* when hourly measures of salary are employed (2006 data). This is the – so called – *raw wage gap* (or alternatively, unadjusted wage gap), which is computed as the difference between men's and women's mean hourly wages[5]. The figure around Europe ranges from a minimum of 4% (Italy) to a maximum of 27%

5. In this case *gross* wages have been used. However, other sources and studies employ *net* salaries.

(Estonia)[6].

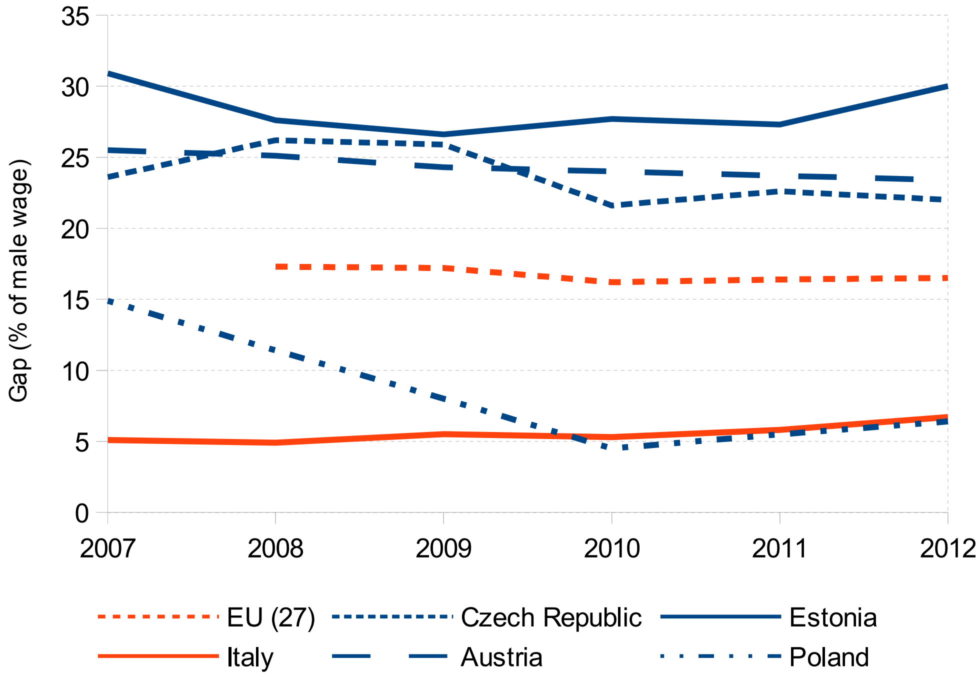
In Figure 2.2 we report the unadjusted gender wage gap trend of some European countries standing out for having particularly high or low pay differentials. In order to make the graph easily readable, we omit all the nations having a gap trend in between the ones reported. At European level, the differential seemed to be narrowing at the beginning of the crisis (roughly until 2010) due to the men being hit by the economic slowdown relatively more than women. In its 2013 report on the effects of the Economic Crisis on Gender Gap, the European Commission observes that at early stages of the downturn the most affected sectors were those in which men were employed in higher number (like construction and manufacturing). Conversely, women-dominated sectors were initially immune. Men's wages were hit relatively more than women's, hence the gap begun to shrink. In addition, the most volatile components of pay (extra payments like bonuses or premia for overtime, that men typically access in higher number than women) were the first to be cut as soon as the crisis kicked off (European Commission, 2013a). The tendency to gap reduction came soon to an end. Between 2010 and 2011 the differential increased again, and is now oscillating around 16,5%.

Estonia is the European country with the highest gender hourly wage gap, and the differential exceeded 30% both, at the beginning and at the end of the time span considered. Austria and Czech Republic come right after Estonia, with a gap ranging between 22 and 27%. On the other side, Italy and Poland are the two European countries registering the lowest unadjusted differential. The Polish gap has been continuously decreasing between 2007 and 2010, gradually losing 10 percentage points. The Italian gap, conversely, has been growing wider in the last

6. The indicator is calculated as $(M-F)/M$ %. This is the official indicator in the Council's report, but we won't use the same formula in the present work. The data source is the SES – Structure of Earnings Survey.

couple of years, and is now around 6%[7].

***Figure 2.2** – Gender Pay Gap in selected European countries in the period 2007 - 2012*



Source: SES (Eurostat)

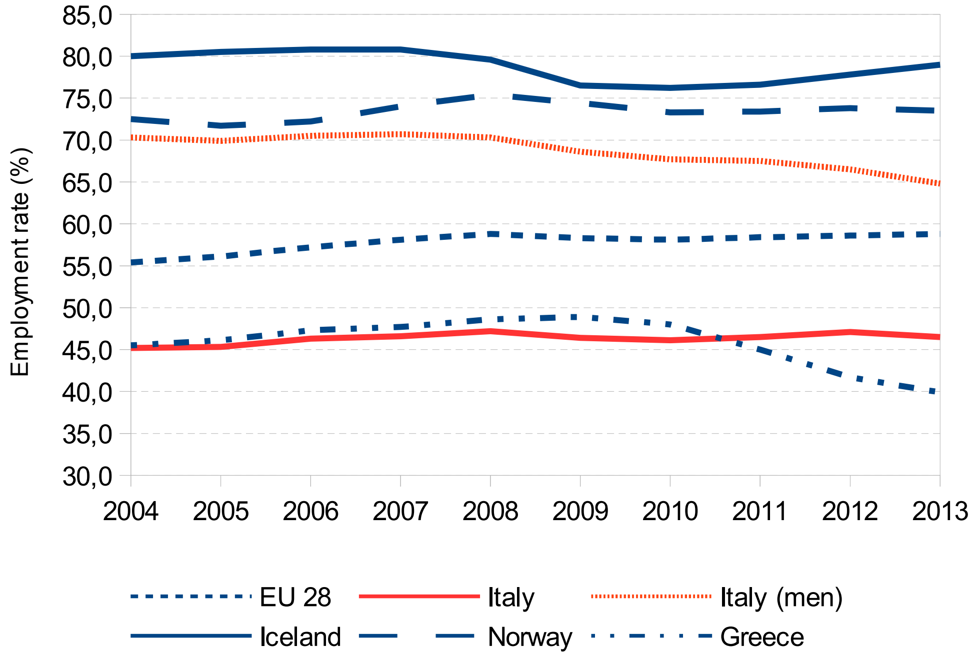
2.3 Participation trends in Italy and Europe

Despite coming nearly first for pay gap, Italy doesn't do as good in female labor market participation. In 2013 women in employment (15 to 64 years old) were less than 50% of the total in Italy, Malta, Croatia and Greece. Figure 2.3 reports the female employment rate between 2004 and 2013. Once again, we

7. Countries like Slovenia and Malta have wage gaps similar to those of Italy and Poland. However, the data were not available for the whole time span here analyzed, hence their trends have not been reported.

chose to include only some countries in Europe standing out for having particularly high or low participation rates. As for the Italian case, we also reported the male employment rate, so to allow for an analysis of the employment gap trend.

Figure 2.3 *– Female employment rate (15-64) in selected European countries in the period 2004-2013*



Source: LFS (Eurostat)

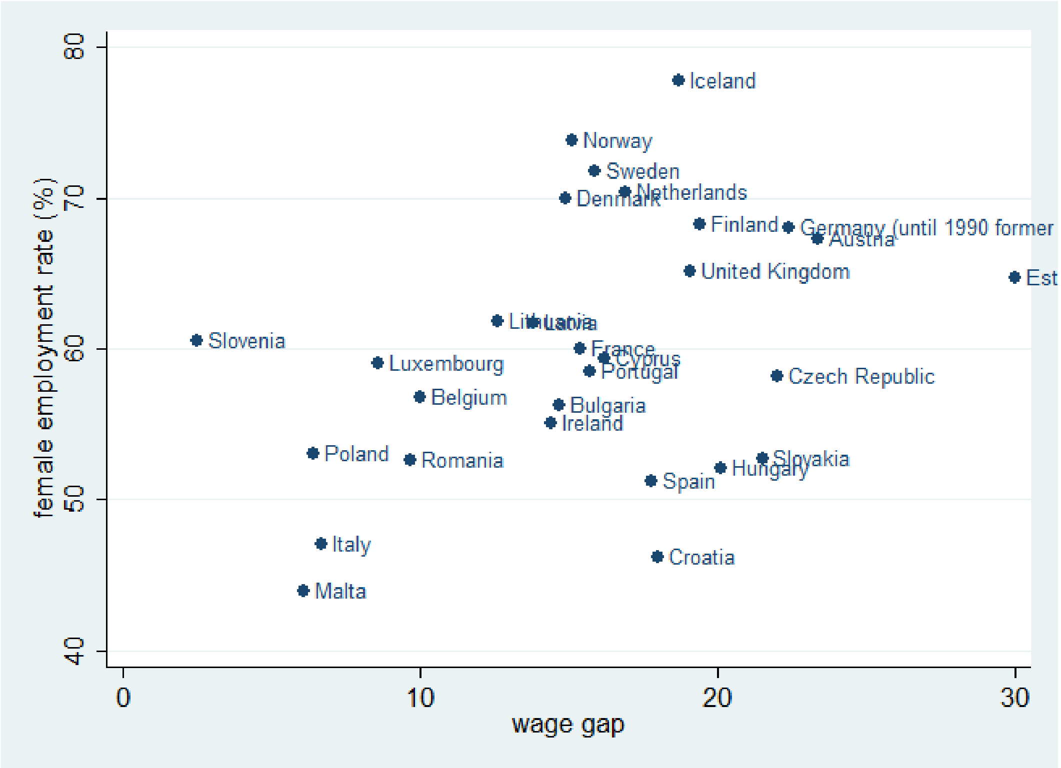
At the top of Europe there are Norway and Iceland. In both these two cases, the employment rate for women is higher than the Italian rate for men. The EU(28) average oscillates between 55 and 60%, while the figure for Italy and Greece ranges between 40 and 50%.

The Italian employment gap has been decreasing throughout the whole time span, although it remains the second highest after Malta (we don't report the correspondent trends here for reasons of readability). The reduction is mainly due to men being employed in lower number since the beginning of the economic crisis. Women, conversely, maintained their employment level substantially unchanged. This tendency matches the European trend, even though at aggregate level the main driver of employment equality has been the increase in female participation (European Commission, 2014a).

By jointly looking at the statistics on participation and hourly gaps in Europe we can notice a strange pattern: those countries doing very bad in the former tend to do well in the latter. Italy is an extreme example, but also in Malta and Poland the wage gap and employment rate have constantly been below 10 and 55% respectively. Figure 2.4 reports the female employment rate versus the gender pay gap in the year 2012.

We can clearly see a positive relation between wage gap and employment rate. In the literature, the explanation usually provided is that in countries with low participation, those women who enter the labor market are also those who can aim for the highest wages. In turn, women in employment receive a relatively high salary and this inevitably keeps the gap down (we will extensively discuss this phenomenon in the next chapters).

Figure 2.4 *– Wage gap versus female employment rate in Europe in 2012*



Source: SES and LFS (Eurostat)

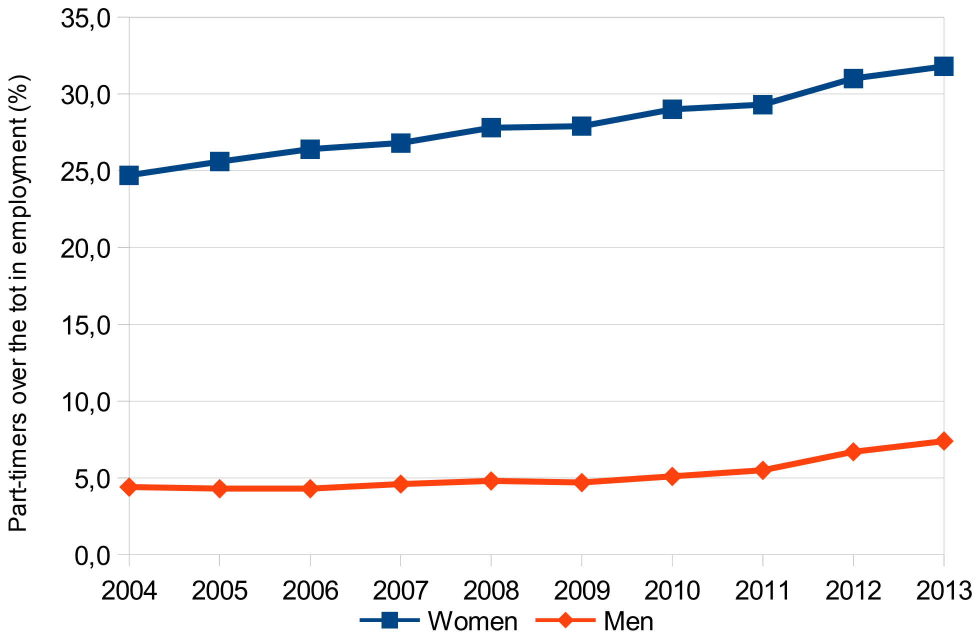
2.4 Annual Pay Gaps and part-time employment in Italy and Europe

Wage differentials can also be studied on an *annual* rather than hourly base. Using yearly payments gives a better idea of what is the actual amount of resources at people's disposal, and how wage gaps impact on individuals' every day life. The Council reports that in 2006 the annual gap in Italy was around 18% in the public sector and 28% in the private sector (Council of EU, 2010)[8]. This is still lower than the European average (respectively 23 and 30%), but sensibly higher than the wage gap obtained by using hourly measures of salaries.

8. In any case the figure does not reach the almost 50% reported by the WEF.

Clearly, annual payments depend on the amount of hours worked, hence part-time employment is an essential factor to be kept in consideration. Working part-time is much more common among women, in Italy as well as in the rest of Europe. In Figure 2.5 we report the percentage of part-timers over the total population in employment in Italy between 2004 and 2013. We can notice an increasing trend for both, men and women. The figure for the former, however, remains significantly lower. Clearly, having a relatively high proportion of women working shorter hours worsens the annual wage gap, although this is not necessarily for reasons of discrimination.

Figure 2.5 *– Percentage of part-timers over the total population in employment in Italy between 2004 and 2013*



Source: LFS (Eurostat)

During the economic crisis, part-time has been used as an alternative to lay-offs (European Commission, 2013a), and led to a disproportionate increase in the number of – so called – involuntary part-timers, among both men and women. This might be the reason why we see a persistent rise in the percentage of population working shorter hours in the last few years (we will discuss the issue in more details in *Chapter 5*).

2.5 Gender segregation in Italy and Europe

Another factor affecting pay gaps is gender segregation. The literature typically distinguishes between horizontal segregation (when women are concentrated in *certain occupations or sectors that pay low wages*) and vertical segregation (when women are concentrated in *low-level positions*). At European level the most female-represented *industries* are "education", "health and social work" and "retail trade and repair of household goods"; while the *occupations* where female participation is highest are "clerical workers", "intermediaries occupations" and "teaching professionals" (Council of EU, 2010).

Vertical segregation, on its side, occurs by blocking access to higher positions for women. The literature usually refers to the two concept of *glass ceiling* and *sticky floor* (Albrecht et al., 2003: Booth et al., 2003). Specifically, the evidence of a larger gap at the top quantiles of the wage distribution is consistent with the *glass ceiling* effect, whereas a larger gap at the bottom is associated with the *sticky floor* effect. The direct consequence of vertical segregation is that of observing unequal salaries at different levels of the wage distribution.

Hakim (2006) observes that vertical segregation (and in this case the *ceiling effect* specifically) does not always occur because of discriminatory behaviors. Hakim claims that women – despite having cognitive ability identical to men – widely differ from their male counterparts in their tastes, values and aspirations. This reflects into their behavior on the work place, and generally keeps them from striving for top careers that require having mainly work-centered lives, with huge responsibilities and working weeks of very long hours.

Surprisingly in Italy gender segregation seems to have effects opposite to what we observe in the majority of the other countries: average salaries tend to be higher in occupations *and* sectors employing mainly women, rather than those employing mainly men (Council of EU, 2010)[9].

At the same time, though, the hourly gap in gross wages favors men in all the cases (female-dominated sectors, female-dominated occupations, male-dominated sectors and male-dominated occupations). This might be the effect of vertical segregation preventing women from achieving high level positions.

Bianco, Ciavarella and Signoretti (2011), focusing again on vertical segregation in top-positions (glass-ceiling), showed that in 2009 not even half of the Italian listed companies had boards with at least one female component, and the overall number of female board members who are women did not go beyond 6,3% of the total (Consob data). In addition, even where boards are gender-diverse the female components tend to have family connections with the leading shareholder. This highlights that women struggle to achieve the top of the career ladder, and when they do so is often because they are advantaged by kinship relations, and not because men's clusters truly desire to pave the way to female colleagues.

The Council of EU studies the glass-ceiling effect by looking at the pay gap at managerial level. In 2006 the Italian figure was around 18% (Council of EU, 2010); in our data the gap is even higher, around 22% (2012).

9. This is not in line with our results: we will see that in our model, when the gap is decomposed and estimations take into account personal and job characteristics, horizontal segregation tends to have *positive* effect on the wage gap (in line with most of the evidence around the World).

In this work we will not deal with the question of gender differences in entrepreneurship. However, for good order, we will briefly cite here the recent findings of the OECD (2012). Despite female employment rate is steadily increasing in OECD countries, women are constantly under-represented as entrepreneurs: in Italy in 2010 the percentage of female employers over the total was only 22%. Even when women decide to start a business, they usually do that on a small-scale and *not* in capital-intensive sectors. The Organization reports that when asked, women cite better work-life balance as one of the main reasons pushing them to start a business. In turn, most of female entrepreneurs at OECD level tend to work shorter hours than men, and they earn around 30-40% less than their male counterparts. In Italy this difference rises to 50%. This suggests that family commitments deeply affect women's aptitudes towards work, no matter if dependent or independent.

2.6 Family responsibility and labor market participation

Summing up, Italy doesn't seems to do that bad on the front of hourly wage gaps and gender segregation (at least relatively to other European countries). The gender pay differential is well below the average, while gender segregation (according to SES data) seems not to be a problem since female-dominated occupations and sectors pay relatively high wages. However, women's participation in the labor market is highly problematic: participation rates are at the bottom of the European ranks, and even those women who enter the labor market, do that as part-timers.

The motivation behind the unequal participation of women and men is probably cultural: women are seen as the main – and sometimes sole – responsible of family-care, and this sensibly affects their ability to work, and to work fulltime. This happens in Italy as well as in the rest of Europe, although in some countries it is more evident. In what follows we report some evidence supporting the hypothesis that women are still in charge of child-caring and household work much more than men are, while men – on their side – take on most of the market-work and the responsibility of income provision.

In a recent study, the European Commission (2014b) found that in all the European countries (except Denmark, Croatia and Slovenia) the status of parent has opposite-in-sign effects on participation between genders. The employment rate of women with children is lower than that of women without, while the opposite is observed for men. The country with the widest difference is Czech Republic: Czech mothers have 30% lower employment rate than women without children, while for fathers the figure is around +7%. The EU(27) average is -11%, +8%, while for Italy this difference is respectively -8% and +12% (EU-SILC 2010 data).

Even when mothers decide to keep working after having a child, in Italy 22% of them declare they have reduced their working hours in order to provide for the newborn. Conversely, only 2-3% of fathers state they have done the same. The EU(27) average is higher: 30% for women and 5% for men reduce their working hours.

As for income provision, all over Europe men are still by far the main breadwinner of the family. On average in EU(27), men provide for at least 60% of the total household income in 58% of the cases. Conversely, women do so only for 14% of the families. The remaining 29% are families in which both the individuals contribute more or less equally (between 40% and 60% each).

In Italy the figure is more polarized towards men. The husband is the main income provider in 65% of the Italian families (one of the highest shares in Europe), although there has been a little tendency towards evening out in the last few years. On the other side, women are the breadwinners in not even 10% of the cases. The remaining 25% is equally distributed.

The European Commission (2014b) also analyzes the number of hours spent in domestic work per week in 11 European countries for which data are available. The results show that: (1) women contribute sensibly more than men, no matter who is the main income earner; (2) the time spent by men in in-house work doesn't increase much if the woman is the main or sole income provider; conversely, women's contribution rises much more steeply as the male partner increases his share in family income provision.

On average, in the 11 countries included in the analysis women spend between 21 and 43 hours a week in domestic work, while men contribute between 11 and 17,5 hours. The same survey does not provide data divided by country, however the OECD (2012) shows that in Italy women spend on average 3,6 hours *a day more than men* in household work.

As we said above, in the next chapters we will not analyze all these issues in details. Instead, our work will be focused on measuring the size of Italy's gender wage gap and its components. However, this kind of study cannot ignore the surrounding framework regarding participation trends, gender segregation etc. All these elements will prove to be fundamental determinants of wage gaps.

Chapter 3
A review of the literature on the Gender Pay Gap in Italy

In this Chapter we will focus on the empirical studies that analyzed the question of GPG in Italy. We will start off with a brief and general introduction of the theoretical explanations for the existence of a gender wage gap. Eventually we will review the most recent and relevant literature studying adjusted and unadjusted wage gaps in Italy. Some possible estimation complications (namely, the selection and endogeneity problems) will be analyzed in details. Finally, we will provide a general overview of relatively new estimation techniques to study the GPG across the wage distribution.

3.1 A theoretical overview of the Gender Pay Gap

The economic theory offers a number of explanations why we observe a wage gap between genders. We believe that before going into details in the study of the empirical works that analyzed the issue in Italy, it might be useful to summarize briefly which are the main theoretical explanations provided.

3.1.1 Preferences, human capital investments and effects on productivity

Different preferences of men and women regarding the division of labor at home *and* on the market might be due to different investments in human capital. In other words, women might (hypothetically) make choices on human capital investments that are completely different from those of men, and this is likely to be eventually reflected on their wages when (and *if*) they enter the labor market. In particular, since the wage gap favors men in all the countries in the world, we might advance the hypothesis that women invest *less,* or invest in educational sectors that lead to careers with lower remunerations. An education in the scientific and technical fields, for example, usually paves the way to careers that pay relatively high wages (and these sectors have traditionally been male-dominated). However, data on education tell a different story: in the recent decades girls have started to outperform boys, especially at University level. In 2012, the percentage of female population in Europe aged 30 to 34 with a University degree was equal to 40% (26% in Italy), while that of men was only 32% (17% in the Italian case)[10]. In addition, women are also less likely to prematurely drop off school: 11% against 14% in 2012 in EU(28). The differential between girls' and boys' performances in science and mathematics is small and keeps shrinking in the last generations (European Commission, 2014a). This contributes to narrow down the gap in scientific faculties enrollment. Furthermore, the OECD (2013 – first wave of the Survey of Adult Skills) shows a little advantage for men in numeracy and problem-solving skills, but the gap

10. LFS (Eurostat)

seems negligible for younger generations. All this makes us believe that the hypothesis of different investments in education doesn't really hold as an explanation for gender gaps. However, apart from education, it is true that women might have lower actual experience on the labor market due to interrupted employment for maternity and child-care. Evidences on this regarding our data will be presented in *Chapter 4*.

3.1.2 Discrimination

The standard theory (Becker, 1957) has modeled discrimination as a consequence of individual preferences (so called “taste for discrimination”). An employer, even in face of equal productivity, might be willing to discriminate, hire a man and pay an extra cost (equal to the wage gap) for it. In theory, this should not constitute a long-term equilibrium since discriminating businesses will not be as efficient as not-discriminating ones, and will be crowded out by competition.

Alternatively, the theory of *statistical discrimination* presents a different framework, where discrimination can survive also in competitive contexts: due to asymmetric, incomplete and costly information employers will use stereotypes to evaluate applicants (Arrow, 1973; Phelps, 1972). Without a reliable measure of individual productivity, firms use gender as an indicator. If the employer expects women to be less present, reliable etc. he will offer a lower salary, slower career advancements, less skilled jobs, and maybe he would even prefer not to hire them at all. Beliefs shape the decisions of employers and keep women in disadvantaged positions. In turn, if women know they can only aspire to low wages and low level positions, they will invest less in education, allocate more time in domestic and care work, and generally behave according to the expectations of the employers (lower commitment, higher absenteeism etc.). We are in a situation of selffulfilling expectations that creates a vicious-cycle of wrong beliefs, lower wages and lower productivity.

3.1.3 Job search and preferences

Del Bono and Vuri (2006) observed that in the nineties in Italy the GPG was usually low soon after entering the labor market. However, it widened and become significantly positive after few years of experience. The explanation proposed by the authors is that in early stages of professional career wages depend substantially from mobility. Job changes tend to be associated with opposite-in-sign wage variations for men and women: the male mobility premium tended to be positive or zero, while the female value tended to be negative. In line with the theory of compensating differentials, the authors speculate that this might be due to the fact that women look for jobs with characteristics that better match their requirements (flexible hours, part-time etc.), even if this means giving up part of their salary. Men, conversely, focus solely on better payments. By repeatedly changing their job, both men and women refine their research towards an occupation with the desired characteristics.

3.1.4 Psychological theories and performance in competitive contexts

We have already cited the work of Hakim (2006) on women's preferences and the ceiling effect in gender segregation. Similarly, a number of recent studies have inspected the possibility that psychological differences between genders could be drivers of wage gaps. Gneezy, Niederle and Rustichini (2003) and Gneezy and Rustichini (2004) conducted laboratory experiments on gender differences in performance in competitive and not competitive environments, and found that men tend to do better in the former context (while no difference arises in the latter). Niederle and Versterlund (2007) found no difference in performance, but observe that women are less prone to competition and tend to self-exclude from situations in which the remuneration is based on the "winner takes it all" principle. These results might not be immediately and unconditionally applicable to the labor market, but they draw attention on the fact that innate aptitudes towards competition actually differ between genders. In addition, Booth (2009) conducted a study on British female students and showed that girls coming from only-female schools (as opposed to those enrolled in mixed schools) have aptitudes towards competition identical to those of boys. This second finding suggests that also the surrounding environment in which men and women grow might shape individuals aptitudes. Clearly, we are interested in aptitudes towards competition because we believe that they could be strong determinants of productivity and, in turn, wages.

As we will see in <u>*Chapter 4*</u>, our work – as well as all the literature that we am presenting further on – will be focused on measuring the size of the GPG and isolating its *discriminatory component*. All the theoretical hypothesis provided above contribute to some extent to explaining the existing gap, and will be taken in good consideration in the development of our analysis.

3.2 Unadjusted and adjusted wage gaps: pooled OLS estimations and the Oaxaca-Blinder decomposition in the Italian literature

The recent literature approached the question of the GPG in Italy from different perspectives. The various works differ by type of analysis undertaken, estimation technique employed and underlying data source. We have already seen how we can simply obtain a measure of the – so called – *raw gap* by computing the difference between the mean wage of men and women. This method offers the big advantage of being extremely simple and immediate. However, the measure does not take into consideration which are the *determinants* of wages and, in turn, wage gaps. For this reasons the raw gap is often referred to as "unadjusted". All the statistics reported so far in the preceding sections were unadjusted measures of the GPG.

Raw gaps present a fundamental problem that Grimshaw and Rubery (2002) describe in a clear and concise way:

> *"[...] the unadjusted pay gap does not compare like with like. The characteristics of men and women in the labor market differ with respect to the length of work experience, the level of education and skills, occupational status and sector of employment. Given that each of these characteristics has some association with the level of earnings, it is assumed appropriate to adjust the pay data so as to distinguish what proportion of the overall pay gap is due to differences in individual characteristics and what proportion is due to sex discrimination within the labor market".*
>
> *[Grimshaw and Rubery, 2002, p.4]*

In principle women might be more or less endowed with characteristics that are typically rewarded in the labor market, hence the adjusted pay gap can potentially be either *higher* or *lower* than the unadjusted.

The literature has approached the problem of "adjusting" the wage gap in two *main* different ways[11]: (1) by performing an estimation of a wage equation for the whole population (pooled) and include a gender control among the regressors; (2) by running two different regressions for men and women and calculating the difference between the two equations, so to isolate the differential due to characteristics from the differential due to discrimination (the – so called –

11. Other techniques not listed here are available, like the Juhn Murphy Pierce decomposition.

Oaxaca-Blinder decomposition). In what follows, we will present the literature employing either methods, starting with the pooled wage estimation.

Addis and Waldman (1996) first developed a comprehensive picture of the gender wage gap situation in Italy, employing a cross-section analysis of the SHIW (Survey on Household Income and Wealth – Indagine sui Bilanci delle Famiglie Italiane) data of the Bank of Italy (first wave, 1989). As the authors observe, before the kickoff of the SHIW no other survey offered a complete set of variables to include in the wage estimations. This impeded the control for characteristics of the worker/job, and in turn the isolation of the discriminatory component.

The estimation technique employed by Addis and Waldman (1996) involved the inclusion of a gender dummy variable in a standard wage equation *à la* Mincer (see Mincer, 1974):

$$w_i = X_i^T \beta + \alpha F_i + u_i$$ [12]

with F_i equal to 1 if the observation is female, and 0 if male. X_i is a vector of controls that are believed to be relevant in explaining the salary level. In this case the authors included age, age squared, three dummy variables for the main educational attainments, a dummy for public sector and a control for the geographical area (North, Center or South). It is important to notice that the authors employed here *annual measures of income as dependent variable*. In order to account for the different provision of labor services, they included a variable for the number of months of work and a variable for the number of weekly working hours.

The parameter relative to the gender dummy represents the estimated adjusted wage gap. The authors found a wage loss of 13% associated with the observation being a woman, *keeping all the other variables constant*. This result is

12. The apex "T" has to be intended as "transposed".

robust to the inclusion of additional controls (a dummy for part time contract and individual indicators for industry and occupation).

In addition to this, Addis and Waldman (1996) add some insights regarding gender segregation. Despite the SHIW coarsely groups occupations in four classes (five in the more recent waves), the authors noticed a disproportionate female participation in the "office workers and teachers" group. The other three classes are all woman under-represented. If it's true that woman-intensive occupations are paid – on average – less than man-intensive, then part of the differential might be imputable to job segregation. However, the estimation technique employed here does not allow us to go much further in investigating this hypothesis. We do observe that the occupations "executives" and "managers" are paid more than "office workers and teachers" (while "blue collars" are paid less), but the returns on the occupational dummies are not differentiated by gender, hence it is not possible to infer who, between men and women, is taking advantage of the wage premium/penalty (in order to extract this information it is necessary to employ the Oaxaca-Blinder decomposition described in the next paragraphs).

Coming to more recent studies, Mundo and Rustichelli (2007) analyzed a long ISFOL dataset[13] spanning the period 1985-2002. They performed a number of estimations on the data, employing slightly different techniques. We will hereby report the main results.

The pooled OLS estimates on (exclusively) 2002 data show a wage gap equal to 13,7%. Thanks to the administrative character of the data source, the authors could count on a number of controls that are usually not available in other databases. These include the tax classification level of the worker, the qualification and the labor collective agreement applied. All these contribute to

13. The database (including only the private sector, agriculture excluded) has been produced in collaboration with INPS (the Italian National Institute for Social Security) and ISTAT (Italian Institute of Statistics).

precisely define the task performed by the worker, so that we do not need to refer to imprecise occupational dummies in order to control for segregation. On the other side, though, the source lacks of controls for individual characteristics that might as well be important determinants of salaries.

The authors also perform a panel random effects estimation on the period 1985-2002 exploiting the longitudinal character of the dataset. This allows them to control for the absence of individual characteristics that the source does not include (just cited above), and individual characteristics that are inherently unobservable (like ability and risk preferences). The result is a 15% pay penalty for women. However, when we look at the data year by year, we notice that the differential has been decreasing slowly but continuously since 1985, starting from values close to 16% and ending around 13,7%. The analysis is integrated with the Oaxaca-Blinder decomposition of the wage gap in 2002 that we will briefly describe further on in this section.

Another important and recent work employing pooled wage estimations is Zizza (2013). The author focuses on the Bank of Italy's SHIW database, spanning the period 1995 – 2008. The results obtained are quite sensible to the variable set included as control. In what follows we briefly summarize the main findings.

When the wage equation includes only a gender dummy (and no other control) the wage penalty associated with the observation being a woman amounts to 4,9 to 7,7% (which can be interpreted as the raw gap). The two extremes values are registered, respectively, in 2002 and 2000. Conversely, when individual characteristics are included (education, potential experience in the labor market and number of different jobs in the working life) the wage-penalty rises to 9,7 to 14,4% (extreme values recorded in 2000 and 2002). The estimates are slightly lower when the features of the job/employer (occupational dummies and size of the company) are added: 7,4 to 11,1%. The author also operates a selection correction for participation in labor market and type of employment (dependent versus independent work). The results range between 9,2 and 13,2%. The selection correction will be analyzed separately in <u>*Section 3.3*</u>.

The findings cited so far are *quantitative measures of the adjusted wage gap*. This because, as we said, the raw wage gap is "purified" from collateral effects due to differences in the endowment of market-rewarded characteristics. However, the alpha parameter that the cited works have been estimating, has to be interpreted "*ceteris paribus",* that means "keeping all the rest constant". In other words, we are comparing two perfectly identical individuals, endowed with *equal characteristics* (education level, experience, occupation, size of the company and so on depending on the controls included), receiving the *same returns* per characteristic, and differing *only by their gender.*

This pooled OLS analysis is somehow limited, since it does not take into account the fact that men and women may differ also in the rewards they receive for the same characteristics. Conversely, the coefficient of the gender dummy captures the whole effect of the gaps in rewards in a single parameter, which is much less informative regarding the source of gender discrimination. In a review of the literature on the estimation techniques employed to measure the GPG in Poland, Van Der Velde, Tyrowicz and Goraus (2013) present the problem as follows:

> *"[...] linear regressions have several shortcomings, such as [...] the fact that men and women might receive different rewards for the same characteristics. This can be controlled for in the linear regression context by adding interaction variables with the gender dummies. This procedure is in practice equivalent to the estimation of two separate equations, and then decomposing the absolute differences in wages into the component attributable to differences in characteristics and component that cannot be*

> *explained by objective differences. The latter is conceptualized as adjusted gender wage gap, often identified with discrimination."*
>
> *[Van Der Velde, Tyrowicz and Goraus, 2013, p.3]*

The procedure described in the quotation – which is supposed to overcome the problem of gender differentiated rewards – is the well known Oaxaca-Blinder decomposition. Oaxaca (1973) and Blinder (1973), building on Becker (1957), proposed this approach that develops in two stages.

First, log wage regressions are estimated separately for men and women:

$$w_i^g = X_i^{g,T} \beta^g + u_i^g$$

with $g=m,f$ (male and female). As before, the vector X_i contains all those controls that we expect might influence wage (personal characteristics, job-related and – if available – household-related factors). $\hat{\beta}$ is the vector of estimated returns.

Second, once we have separately estimated the parameters for men and women, we can differentiate male and female average log-wage and write the pay gap as follows:

$$\bar{w}^m - \bar{w}^f = \bar{X}^m \widehat{\beta^m} - \bar{X}^f \widehat{\beta^f}$$

By adding and subtracting the term $\bar{X}^f \widehat{\beta^m}$ we obtain the gap decomposition:

$$\bar{w}^m - \bar{w}^f = (\bar{X}^m - \bar{X}^f)\widehat{\beta^m} + \bar{X}^f(\widehat{\beta^m} - \widehat{\beta^f})$$

It is important to keep in mind that the choice of $\widehat{\beta^m}$ in the added term $\bar{X}^f \widehat{\beta^m}$ is *arbitrary*. Other choices have been taken in consideration in the preceding literature: Neumark (1988) uses the coefficient estimated on the whole sample of men and women (pooled estimation coefficient); Reimers (1983) suggests to employ a simple average of the men and women parameters; Cotton (1988) proposes an average weighted on the proportion of each sex in the sample.

Clearly, if we change the addendum, in turn also the first term of the decomposition will change. Since the estimated coefficients for women and men differ (because of potential discrimination), we expect that the size of the first addendum would be extremely sensible to our choice. However, most of the literature employs the men's coefficients (classic Oaxaca methodology), and for reasons of comparability we will follow this same standard in the present study.

The raw gap is now decomposed in two parts: the first term captures the "*endowment effect*" (i.e. the difference in the mean value of each characteristic weighted on men's returns), and the second term captures the "*coefficient effect*". The latter is sometimes referred to as "unexplained component", and it includes two elements: the difference due to *unobservable factors* (the intercepts in the men and women equations) and the difference due to *gender differentiated rewards for equal characteristics* (basically, all the other coefficients apart from the intercepts).

The coefficient effect represents the adjusted gender wage gap, and it is often interpreted as discrimination. Clearly, as long as discrimination arises among observable factors, we can directly impute it to the differentiated treatment of women and men with respect to a specific characteristic. Conversely, when discrimination is due to unobservable (intercepts), we cannot be totally sure of its origins, and the interpretation might be debatable. It is evident that the choice of the variables to be included in the wage regressions has a direct impact on measuring and interpreting discrimination. This has been noted by Oaxaca (1973) in its seminal work, where the author clearly states that a researcher's choice of the control variables implicitly reveals her or his attitudes with respect to what constitutes discrimination and what does not.

A number of recent studies employ the Oaxaca-Blinder decomposition. We will present here the most relevant for the Italian case.

Addabbo and Favaro (2007) use Eurostat data from the European Community Household Panel (ECHP) relative to 2006. The set of regressors employed in the estimation of the male and female wage equations include education, experience, tenure, occupational and sector controls, contract type (part-time, public sector, permanent or temporary contract etc.), company size and geographical area. Moreover, the authors perform a selection correction for the in/out labor force choice (I will discuss the correction *Section 3.3*).

They find a raw gap around 5,5%, with an endowment effect of -9% and a coefficient effect of +18% (the remaining -3,5% is due to selection bias correction). It is important to notice how the adjusted gap (coefficient effect) is more than three times as big as the unadjusted. This means that discrimination against women is much higher than raw gaps seem to suggest. Moreover, a negative endowment effect indicates that women are on average more endowed with characteristics rewarded in the labor market than men are. So if they actually received the same returns as man, we would observe a pay differential in their favor. The reason why this does not happen (and the gap is actually in men's favor) is that indeed women do not obtain the same rewards as men. The discrimination (captured by the coefficient effect) is high enough to more-than-compensate the endowment effect.

Centra and Cutillo (2009) perform a similar kind of analysis on ISFOL data relative to 2007[14]. The set of controls employed is very similar to that of Addabbo and Favaro (2007), and the correction applied includes the in/out choice and the decision to be employed in a “typically female job” (once again, we will explain in details the correction further on, in *Section 3.3*). The estimated endowment and coefficient effects amount to – respectively – -2% and +10,8%

14. The data have been collected with an *ad-hoc* survey by ISFOL named “Gender Pay Gap Survey” whose construction started in 2005 and ended in 2007 with the data collection.

(net of the selection correction). Once again, the former is negative, but the latter is high in enough to compensate.

Mundo and Rustichelli (2007) complete their analysis of ISFOL data presented in the previous chapter with an Oaxaca-Blinder decomposition on selected years between 1996 and 2002[15]. Moreover, they perform some controls on the estimates by changing the weight of the endowment effect (Neumark, Reimers and Cotton methodologies). They find that the endowment effect ranges approximately between -0,2 and 2,5%, depending on the year and the method applied. Conversely, the coefficient effect (adjusted pay gap) varies between 5,4 and 7,2%, once again depending on the year and method.

Pissarides at al. (2005) carry out a complete analysis of the situation of the gender wage gap in European countries using the 1998 ECHP database. They observe that Mediterranean countries like Spain, Italy and Greece are extremely sensible to the adjustment of raw gaps. For Italy unadjusted and adjusted differentials are – respectively – 8,5% and 16%. For Spain, 14 and 31%. For Greece 11 and 31%. Conversely, in many other European countries (Nordic and German speaking in particular), the raw gap exceeds the adjusted estimates by some percentage points. On one hand, we can expect that part of the difference between adjusted and unadjusted estimates is due to the control for different endowment of characteristics that the Oaxaca-Blinder decomposition makes possible. But more than that, as the authors observe, the difference is due to the correction for participation choice, which is particularly relevant for Mediterranean countries (see the data on female and male employment reported in <u>*Chapter 2*</u> and the technical comment in <u>*Section 3.3*</u>).

The Italian Institute of Statistics (ISTAT), in its annual report on 2004 (ISTAT, 2005), measures a 16% raw wage gap between sexes (reference year:

15. Please note that the dataset is *not* the same analyzed by Centra and Cutillo (2009).

2002), which is decomposed in 4,8% endowment effect and 11,2% coefficient effect (adjusted pay gap). The data source (SES) is particularly rich of job/employer-related controls, but it does not provide extensive information on individual characteristics. This could partially affect the comparability of the results with the rest of the literature. Moreover, the survey only includes employees of firms with at least 10 workers, and this might be a serious problem given the typical micro character of most of the Italian businesses.

Beblo et al. (2003) employ 1998 ECHP data (limiting the analysis to 25-55 year old individuals) and found a raw gap around 6,8%, of which 10,2% is the coefficient effect and -3,4% is the endowment effect. Again, the estimation technique employed involves a correction for the in/out employment decision.

Before starting to analyze the technicalities of the selection corrections applied by most of the works just cited, we will provide a summary table (*Table 3.1*) of the main studies that estimated the adjusted and unadjusted wage gaps in Italy in the last years. The purpose is that of presenting the findings in a clear way and try to spot possible similarities among the results.

In reading the table it is important to bear in mind some remarks: (1) the gaps are expressed here (and in the rest of the work) in *percentage of the women's wage*. This is not common to all the literature: sometimes the differential is reported as share of men's wage; in some other cases only the wage-penalty associated with the observation being a woman is presented, hence it is necessary to adjust the calculations. So far the findings have been reported as they were presented in the original works. However, in the table they will be adapted to the common standard; (2) the coefficient effect is already net of selection correction (where present); (3) the endowment effect is weighted on men's characteristics (original Oaxaca methodology); (4) as I've already pointed out multiple times, the coefficient effect identifies the adjusted pay gap, while the raw differential corresponds to the unadjusted GPG; (5) all the data are expressed in percentage points; (6) we reported only those works whose main purpose is to measure the mean adjusted wage gap. Other studies focusing on the estimation of the gap in different points of the salary distribution will be analyzed in <u>*Section 3.4*</u>.

Table 3.1 *– Summary of the main results from the Italian literature*

Reference	***Data Source***	***Ref. year(s)***	***Model***	***Raw Gap***	***Coeff. effect***	***End. effect***
Addis and Waldmann (1996)	SHIW	1989	Pooled OLS on annual gross income		12,1	
Flabbi (2001)	SHIW	1977	Oaxaca-Blinder on annual net income	29,4	15,9	13,4
		1995		18,9	13,8	5,1
Beblo et al. (2003)	ECHP	1998	Oaxaca-Blinder on annual gross income (with selection correction)	6,9	10,4	-3,5
Pissarides et al. (2005)	ECHP	1998	Oaxaca-Blinder on hourly gross wage (with selection correction)	8,5	15,9	
Olivetti and Petrongolo (2005)	ECHP	1994-2001	Accounting of the impact of the selection correction	5,2 to 41,4 (potential)		
Rustichelli (2005)	INPS	1996-2002	Random Effects panel estimation on daily wage	18,0	16,0	2,0
Mundo and Rustichelli (2007)	INPS-ISFOL	2002	Pooled OLS on daily gross wage		13,7	
		1985-2002	Random Effects panel estimation on daily wage		15,0	
		1996-2002	Oaxaca-Blinder on daily gross wage	6,9 to 7,5	6,7 to 7,2	-0,2 to 0,8
ISTAT (2005)	SES	2002	Oaxaca-Blinder on hourly gross wage	16,0	11,2	4,8
Addabbo and Favaro (2007)	ECHP	2007	Oaxaca-Blinder on hourly gross wage (with selection correction)	5,5	14,5	-9,0
Centra and Cutillo (2009)	ISFOL	2007	Oaxaca-Blinder on hourly net wage (with selection correction)	8,7	10,8	-2,1
Zizza (2013)	SHIW	1995-2008	Pooled OLS on net hourly wage (with selection correction)		8,7 to 12,3	

Trying to perform a general comparison of the results is extremely difficult. The analyses reported widely differ under many dimensions: the dependent variable (gross or net, hourly or annual), the estimation technique employed (pooled OLS, pooled panel estimation, Oaxaca-Blinder decomposition), the selection correction applied, the sample considered (especially the age interval of the interviewees), the nature of the source (survey or administrative source), the reference year(s) and, last but not least, the type and number of controls available.

Generally speaking, we can observe that as long as the Oaxaca-Blinder decomposition is employed, the endowment effect resulting from the estimations tends to be relatively small and negative. This occurs in Centra and Cutillo (2009), Addabbo and Favaro (2007), Beblo et al. (2003) and (with some *caveats*) in Mundo and Rustichelli (2007). When annual income is compared, it is important for comparability that the regressions include at least some controls for the number of months and weekly hours worked, in order to correct (even partially) for individuals working shorter hours (see *Chapter 2* for some data on part-timers). This is indeed the case in Beblo et al. (2003) and Addis and Waldmann (1996).

The adjusted wage gap tends to range within the band 10-15% (although there are some outliers) and is generally higher than the unadjusted measure. The raw gap, conversely, is lower than 9% in most of the cases. There are some exceptions: ISTAT (2005) which employs a very particular dataset (SES), and Rustichelli (2005) and Flabbi (2001) who employ daily and annual measures of salary.

3.3 Selection correction and endogeneity problems

In the previous section we cited a number of empirical works employing a variety of corrections to the OLS estimates (being them in the pooled OLS method or in the Oaxaca-Blinder decomposition). We will hereby discuss these techniques, starting with the in/out labor-force selection model.

In *Chapter 2* we showed how countries with low female participation rates tend also to have low wage gaps. Pissarides at al. (2005) argue that this might be due to cross-country differences in how women self-select into employment. The southern area generally has a lower participation rate, and this might be caused by a peculiar cultural aptitude towards female employment. It is well established in the literature that low participation leads to statistical complications, since the sample of individuals in employment (on which the wage equations are estimated) is not random. In particular, we might expect those women who choose to work (and for whom the wage is recorded) to be also those who can aim to the highest salaries (for example, those who invested most in education). If this is true, women in the labor force will be systematically different from women outside: they will be on average more endowed with those characteristics rewarded in the labor market. The sub-sample of subjects in employment won't be representative of the whole population, and this will lead to biased OLS estimates.

I will try to explain the problem clearly by dividing it in multiple steps:

- Generally speaking, most of the male population wants to work. If men are not in employment is usually because they are looking for occupation (unemployed), they are not in working age (students and retiree) or they are particularly wealthy, volunteer workers etc. It is extremely rare to observe male “housewives”.
- For various reasons, not all the female population self-selects into employment. We have already pointed out how women devote much more time than men to household production. In some cultures this is more “accepted” than in others, so it is more likely to observe a large number of housewives.

- It is reasonable to expect that those women who decide to work are also those who expect to earn more.
- If the salary offered by the employer is below a certain reservation wage, women just stay at home. The female reservation wage might be higher than men's for cultural reasons, but also because women tend to have higher productivity in home-production, hence they prefer to substitute market work with home work.
- Employed women will be highly endowed with market-rewarded characteristics, and will earn a (relatively) higher salary than that women outside employment could have earned. Hence, employed women are not representative of the whole female sample.
- The selection problem is relevant for wage differential studies because it makes the pay gap narrower than we could expect it to be if all the women where included in the estimation sample.

It is possible to correct for this by employing a sample selection model *à la* Heckman (1976, 1979). The correction concerns only the women sample, since – as we said – there is almost no man voluntarily choosing to stay at home[16]. The methods develops in two steps that we will present in what follows.

In the first step we model the probability of being employed by means of the – so called – *selection equation*. The selection mechanism is controlled by the unobserved continuous utility function P_i° :

$$P_i^{\circ}=A_i\alpha+e_i$$

where A_i is a vector of controls affecting the participation decision, and α is the vector of the marginal utilities of each control included. Usually the explanatory variables employed include individual characteristics (education, age,

16. In our database (SHIW 2012), for example, only 3 men are male “housewives”.

marital status, area of residence etc.) and household characteristics (the number of young children in the household, number of income earners, total components of the family etc.). The utility function is negative or zero if the subject does not work, and positive otherwise. However, P_i° is unobserved. What we do observe is the binary variable P_i that is used in the estimation equation instead of the true values of P_i° :

$P_i = 0$ if the woman does not work (that is $P_i^{\circ} \leq 0$)

$P_i = 1$ if the woman works (that is $P_i^{\circ} > 0$)

Once we have run the regression and estimated the coefficients vector we can calculate the Inverse Mill's Ratio (IMR):

$$\hat{\lambda}_i = \varphi(A_i \hat{\alpha}) / \Phi(A_i \hat{\alpha})$$

which is the ratio of the probability density function and the cumulative density function of the normal distribution evaluated at the predicted outcomes. The IMR serves as correction term in the wage equation.

The second step is the estimation of the female wage equation:

$$w_i^f = X_i^f \beta + u_i^f$$

However this is observed only for women in employment, hence:

$$E(w_i^f | X_i^f, P_i = 1) = X_i^f \beta^f + E(u_i | A_i \alpha + e_i > 0) = X_i^f \beta^f + E(u_i | e_i > -A_i \alpha)$$

The second addendum is equal to $\theta \hat{\lambda}_i$ which is the IMR (correction term) and its relative coefficient, and it accounts for the errors of the participation and wage equations moving in the same direction. In other words, we are controlling for the fact that the same factors explaining the participation choice could also explain wages. Accordingly, we would expect the correction term to have positive sign, which means that individuals with higher probability of being employed are also those who earn more.

The use of this technique allows us to overcome a huge hurdle for international comparisons of wage gaps, since uncorrected differentials could be severely biased and provide a distorted picture of a country's situation. Pissarides et al. (2005), for example, show how much the correction impacts on EU Mediterranean countries, as opposed to Nordic countries. It is clear that once the raw differentials have been adjusted and corrected, the international picture of the GPG across countries might be sensibly different. Italy, for example, might not retain its position among the most egalitarian countries in Europe.

However, the selection in employment is not the only technical problem. The literature drew attention on the fact that gender segregation has consequences on the size of the gap, and in particular female-dominated positions pay low wages. This might happen for various reasons, that can be grouped under three headings.

- Bergmann (1974) suggests that when women are forced into few occupations, the supply of female work tends to exceed the demand and inevitably lower the wages received (*crowding hypothesis*).
- Filer (1989) advances the hypothesis that women have a preference for (and tend to self-select in) jobs that require lower investments in human capital because they forecast a more intermittent professional life than men do. Or similarly, they prefer jobs characterized by slowly deteriorating human capital investments, so that the skills acquired will not worsen drastically in case of pregnancy leaves. Clearly, these job-characteristics might be associated with lower productivity and, in turn, lower wages.
- It may also be the case that – as we have already commented in *Section 3.1* – women pay less attention than men to the entity of the pay, and more to other factors (like the flexibility of the working hours). Hence they will take on jobs paying relatively low wages as long as they offer these

additional conditions.

Having low wages in female-dominated occupations or sectors affects the size of the gender gap. However, in the second and third circumstances considered above, being employed in these positions is consequence of a free choice. Hence, we cannot exclude the possible presence of endogeneity. The problem, in particular, arises when factors explaining the wage can also influence the occupational decision.

Centra and Cutillo (2009) control for endogeneity by explicitly modeling the probability of being employed in a typically female job (i.e. an occupation in which the share of women over the total is particularly high)[17] in a secondary regression (two-stage least square). The authors first include a binary variable assuming the value 1 when the occupation is female-dominated in the wage equation. Secondly, they substitute this regressor with the predicted values from the secondary estimation, and they run the wage regression with them.

Zizza (2013) takes into consideration another kind of choice, which is once again the result of free decision: being an employee or being self-employed. This choice seems to be particularly relevant in the Italian setting, where we observe a significant share of self-employment. Zizza distinguishes between a first stage, in which she models the probability of working versus not-working, and a second stage, in which she models the probability of being dependent worker versus self-employed. The two equations are estimated simultaneously using a maximum-likelihood approach. The exclusion restrictions of the second stage are the level of risk-aversion and the self-employed status of (at least one of) the parents.

17. Remember that this correction might concern the men sample as well as the women sample. We don't have reasons to exclude the possibility that also men might want a job with – say – flexible working hours.

3.4 The Gender Pay Gap along the wage distribution

A limitation of the Oaxaca-Blinder decomposition is that, by studying the difference between *mean* wages of men and women, it implicitly assumes that the gap is constant throughout the whole wage distribution. The mean measure is not informative on the size of the differential in different points of the distribution. In principle, the gap might be sensibly higher or lower (or even reversed) depending on the segment of the distribution in analysis.

Arulampam, Booth and Bryan (2005) study the issue of GPG estimation along the wage distribution by sector (private and public) in 11 European countries. The database employed is the ECHP (pooled waves between 1995 and 2001), and the estimation technique is the Quantile Regression (QR), which allows the authors to track the trend of the adjusted gap along the distribution. If the main advantage of the Oaxaca-Blinder decomposition (with respect to pooled OLS linear estimates) was that we could control for different characteristics returns between genders, here the returns can vary also between quantiles:

$$Gap(\gamma)=\bar{X}^{m}(\gamma)[\widehat{\beta^{m}}(\gamma)-\widehat{\beta^{f}}(\gamma)]$$

where γ is the quantile in analysis. One remark to keep in mind is that the difference in coefficients is here weighted on men's characteristics (and not on women's as we saw in the other works so far).

The results are particularly interesting, both at European and Italian level. In the Italian public sector the pooled OLS estimation on the whole period, records a 11,8% pay loss for women as average of the entire wage distribution. However, the gap is continuously increasing, from a minimum of 8,6% in the first decile, to a maximum of 22% in the last, when QR estimation is employed. In the private sector, conversely, the differential is higher at the extremes: 19,4% and 23,5% in the first and last deciles, while it doesn't go beyond 17% in the middle of the distribution.

Similarly, the European tendency is to observe either increasing or U-shaped gaps, although the differential recorded on the left extreme is always lower than that on the right. These findings confirm the existence of a ceiling (and sometimes also a sticky floor) effect throughout Europe. In addition, it is confirmed that once we adjust the estimates, Italy does not retain its position as one of the top European countries for lowest gender gap.

Addabbo and Favaro (2007) integrated their Oaxaca-Blinder analysis of ECHP data with a QR estimation by level of education achieved. The dependent variable in this case is the annual income (although the authors include controls for months and hours worked). The sample (relative to 2001) is split in two sub-groups: individuals who achieved (at most) high-school level education, and individuals that went on with tertiary education. The gap is higher in the former case and lower in the latter. However we see some trends within groups: lowly educated women suffer both, the sticky floor effect in the first quantiles, and the glass ceiling in the last. Highly educated subjects have continuously increasing gaps proceeding in the wage distribution (so, only glass-ceiling effect).

The results do not differ much from those of a preceding work by De La Rica, Dolado and Llorens (2005), who performed the same kind of QR estimation divided by educational attainments on Spanish data (ECHP) relative to 1999. Despite the country in analysis is different, the findings of the two studies are very similar, and the same interpretation can be applied to the phenomena observed. We will report here some lines from De La Rica, Dolado and Llorens (2005) that offer a comprehensive description of the evidence in light of the theories of discrimination we have seen so far:

> *"Due to the historical low participation of women in the L-*

> *group*[18]*, employers may use statistical discrimination to lower their wages vis-à-vis more stable men in the lower part of the wage distribution since they expect future career interruptions to jeopardize their financing of specific training. However, as their job tenure expands, women become more reliable to employers' eyes and their wages converge to men's wages with the same characteristics. By contrast, women in the H-group, who have undergone a costly investment in human capital, can be expected to be more stable, since their participation rate is much larger, and therefore are less discriminated at the bottom on the wage distribution. However, for reasons related to their lower job mobility or bargaining power, they suffer from larger gaps at the top of the distribution. Hence, there seems to be a "composition effect" in the overall gender gap, when both groups are lumped together: while there is a glass floor the L-group, there is a glass ceiling for the H-group."*
>
> *[De la Rica, Dolado, Llorens, 2005, p.16]*

Favaro and Magrini (2005) analyze a sample of young workers aged 15 to 29 during the period 1990 to 1997. The data are made available by the Italian Institute of Social Security (INPS), and are relative to the sole provinces of Treviso and Vicenza. As I've described previously, the administrative character of the data source makes it possible to compare individuals having exactly identical positions. The estimation technique is slightly different from the QR, and involves a comparison of the distributions of estimated and reference earnings in order to extract a measure of the actual discriminatory component of the gap. As in Addabbo and Favaro (2007), discrimination is lower for highly educated groups. In addition, it is possible to spot a positive correlation between discrimination and level of general and specific human capital (experience and tenure).

18. L-group stands for "low education group", while H-group means "high education group".

Chapter 4
Data, variables and estimation technique

In this chapter we will present the database and the estimation technique employed in our analysis. Eventually, we will provide a detailed description of the controls that the data source makes available.

4.1 Dataset and estimation

The purpose of this work is to investigate the size of the adjusted wage gap and offer a complete analysis of the impact of discrimination on women's salaries. The estimation technique employed is the Oaxaca-Blinder decomposition alongside with the Heckman correction for the participation choice. The raw pay gap will then be decomposed as follows:

$$\bar{w}^m - \bar{w}^f = (\bar{X}^m - \bar{X}^f)\widehat{\beta^m} + \bar{X}^f(\widehat{\beta^m} - \widehat{\beta^f}) - \hat{\theta}\,\bar{\lambda}_i$$

The differential is split in three parts: the first addendum is again the endowment effect, accounting for the difference in mean values of men's and women's characteristics weighted on men's returns (classic Oaxaca methodology). The second part is the coefficient effect, accounting for discrimination in returns and weighted on mean female characteristics. The third part is the correction term already discussed in the previous chapter.

The database analyzed is the last available wave (2012) of the SHIW of the Bank of Italy. Data from the same source have been used in other works reported in the literature review, but none of them is updated to 2012.

The sample includes 2787 male dependent workers, 2238 female dependent workers and 1674 female housewives. We chose only employees because we are investigating the effects of discriminatory behaviors by employers on female wages, hence considering self-employment would be pointless. As for housewives, there is the need to identify a group of individuals that freely chose to stay at home instead of pursuing a professional career. In addition, only individuals in the age interval 23-64 are included in the analysis. This is to limit the influence of complexities in the labor market choices of subjects at the extremes of their working lives: individuals younger than 23 might be in a mixed study-work situation, while subjects older than 64 might be working shorter hours due to retirement. Both the circumstances are likely to affect wages in abnormal ways.

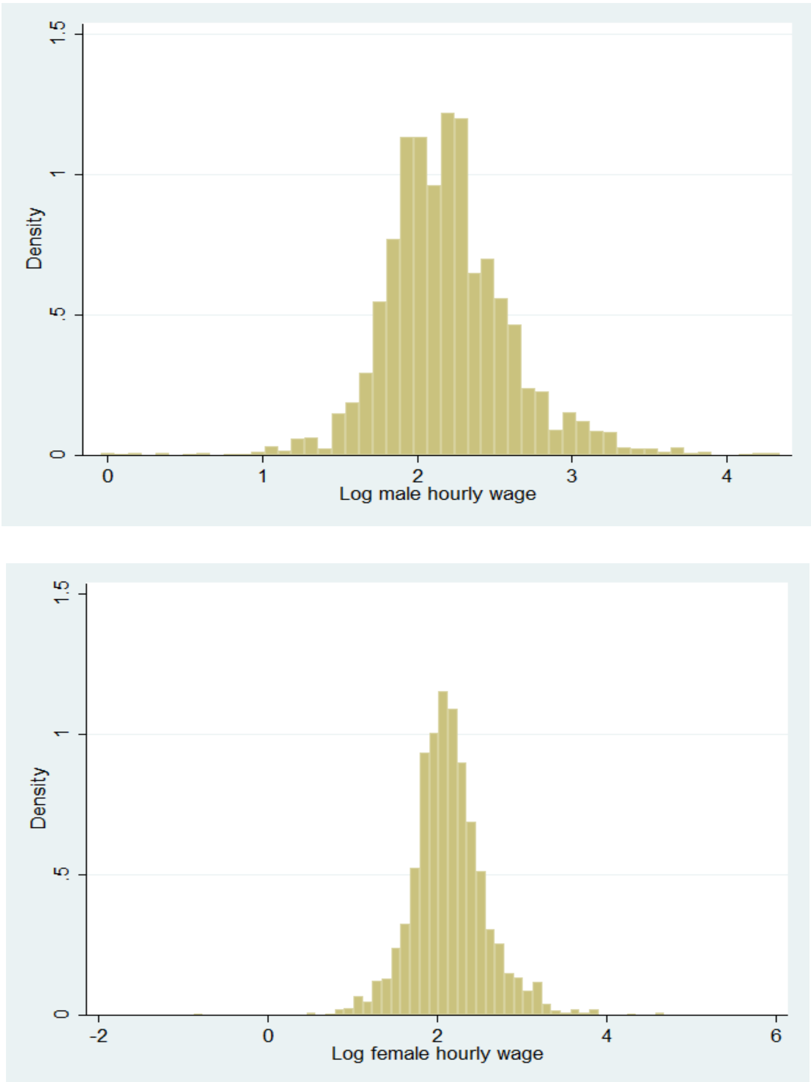
The dependent variable is the net log hourly wage. The SHIW only provides data on the total net annual income from dependent work[19], alongside with the weekly hours worked (regular + extra) and the total number of months in employment. The calculation of the hourly wage can only be indirect, and this

19. Since all the data on occupation, sector, contract type etc. are assumed to be referring to the primary occupation, we ignored compensations for secondary jobs. Few observations (15 in total) reporting more than one primary job have been dropped.
The annual income is net of severance payments, social security and welfare contributions, tax deductions and meal vouchers, but it includes compensations for extra-hours.

exposes us to high risk of *measurement error*. *We* will provide further comments on the issue in the critiques section of *Chapter 5*.

In Figure 4.1 we show the distribution of log hourly wages of men and women in employment.

Figure 4.1 *– Distribution of log male and log female hourly wages*



Source: SHIW 2012

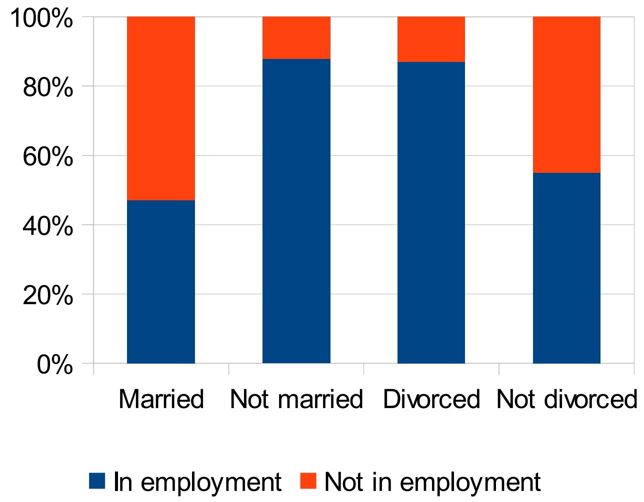
4.2 Available controls

The SHIW includes a large number of relevant wage determinants. The choice of variables to include in the regressions can sensibly affect the size of the estimated gap, hence it is important to select accurately what to add and what to leave out.

In what follows we will present in details all the available variables, starting with controls for individual characteristics:

- *Age:* a continuous variable counting the years of age will be included in the wage equation and also in the regression controlling the selection in employment. However, since we might be interested in looking at the wage premium/penalty by age class (for example, we may want to know how much more does a middle age worker earn with respect to a young one), we also created four dummies for the intervals 23 to 34 (used as base), 35 to 44, 45 to 54 and 55 to 64.
- *Citizenship*: a dummy being equal to one if the observation is Italian citizen is included in both the regressions. A significant positive parameter in the wage equation can signal the presence of discrimination against non-Italians (all the rest being equal). Non-zero estimates in the participation equation can reflect differences in cultural aptitudes towards labor force participation between Italians and non-Italians.
- *Marital status*: we consider two dummies for marital status: “married” and “divorced”, and we will include them in the participation regression. We expect being married to have negative effects on participation, due to family duties. Conversely, divorce might encourage women to go back to employment for economic reasons. Figure 4.2 shows the distribution of women in and out employment by marital status.

Figure 4.2 *– Distribution of employed and not employed women by marital status*



Source: SHIW 2012

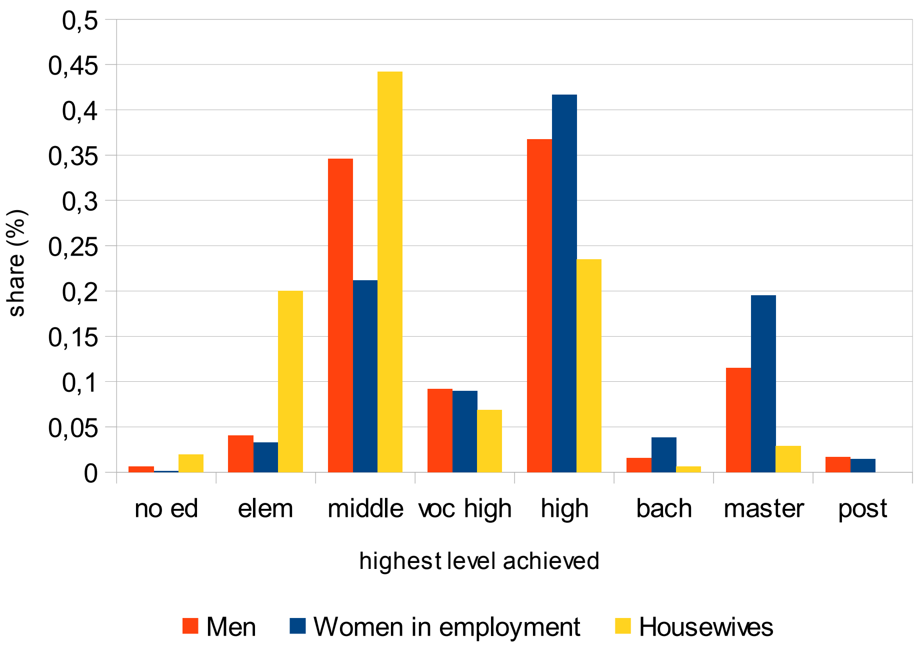
They data seem to confirm our hypothesis. There actually are more individuals out than in employment among the married women. Conversely, not married individuals are mostly in employment. Also, divorce makes it more likely for women to be working[20].

- *Education:* seven educational attainments are considered (plus "no education" used as base): elementary school, middle school (scuola media), vocational high school, high school, bachelor degree, master degree and doctorate studies. Education is included in both the equations: on the wage side, we expect schooling to be correlated with productivity (and productivity to equal pay, according to the Neoclassical view); on the participation side, we can envisage that highly educated individuals will expect wages above the reservation level, and thus be more likely to be in employment.

20. Clearly, this is not a "*ceteris paribus*" analysis, hence we cannot draw any final conclusion.

Figure 4.3 illustrates the gender distribution per educational attainment.

Figure 4.3 *– Distribution of men, employed women and not employed women by educational attainment*



Source: SHIW 2012

We can immediately notice how the investment in education differs between classes. Almost 45% of the women not in employment did not continue after middle school. Around 23% stopped at high school, and only a negligible share have a degree. However, we have to bear in mind that the level of education (as well as the type of occupation) might reflect (at least to some degree) pre-market discrimination: cultural factors and family influence, for example, can direct schooling choices of young girls. Furthermore, women forecasting lower wages because of discrimination are less encouraged to invest in education, creating a vicious-cycle of low wages and education disinvestment. Also the men's and employed women's distributions widely differ. A large share of the male population stops at middle school (almost 35% against only 20% of the women). Most of those who go on, eventually interrupt their school life with highschool (37% vs 42%), or with the Master Degree (11,5% vs 19,5). Employed women are – on average – *fairly* more educated than men and *way* more educated than other women outside the labor market. This confirms the hypothesis that a selection correction is necessary for our database, because the distribution of characteristics is highly unequal between groups. For good order, it is important to notice that housewives tend to be significantly older than women in employment. This suggests the presence of a generational effect: younger women are more likely to be educated *and* in employment, while older generations are less educated *and* not in employment. Inter-generational cultural aptitudes towards education and work are probability at the base of this phenomenon.

- *Experience:* the survey lacks a measure of the actual labor market experience accounting for the continuity of the employment history. The variable "exp" that we will employ in the wage regression, is calculated by subtracting the age at which the professional career started from the current age (so called "potential experience"). However, some stops might have occurred in between these two moments[21]. Zizza (2013) includes a variable accounting for the number of different job experiences as a proxy for the actual experience. We don't agree with the claim that this should be a valid substitute[22]. Plus, we have already observed how changing many

21. The survey actually includes the number of years of unemployment, but it doesn't specify whether these moments occurred before or after the career beginning. The simple subtraction of the unemployment years from experience might result in negative values of "exp".
22. Changing many jobs doesn't necessarily have to be correlated with a longer labor market experience. Instead, cultural factors may affect the decision to change/retain a job.

jobs might have different effects in the two sub-samples of men and women due to unequal preferences regarding the desired job characteristics. However, this only concerns the *interpretation* of the effect, and not the *importance* of the variable in explaining wage determination, hence the number of work experiences will still be included as regressor alongside with the potential experience. Finally, the survey makes also available the job tenure, which accounts for the accumulation of job-specific skills and could definitely be a relevant wage determinant. However, the record is missing for almost half of the observations, hence we preferred to omit this control. Since there are reasons to doubt the degree of reliability of each and every of these variables, we ran a number of regressions with different var-sets to test for the robustness of our findings[23].

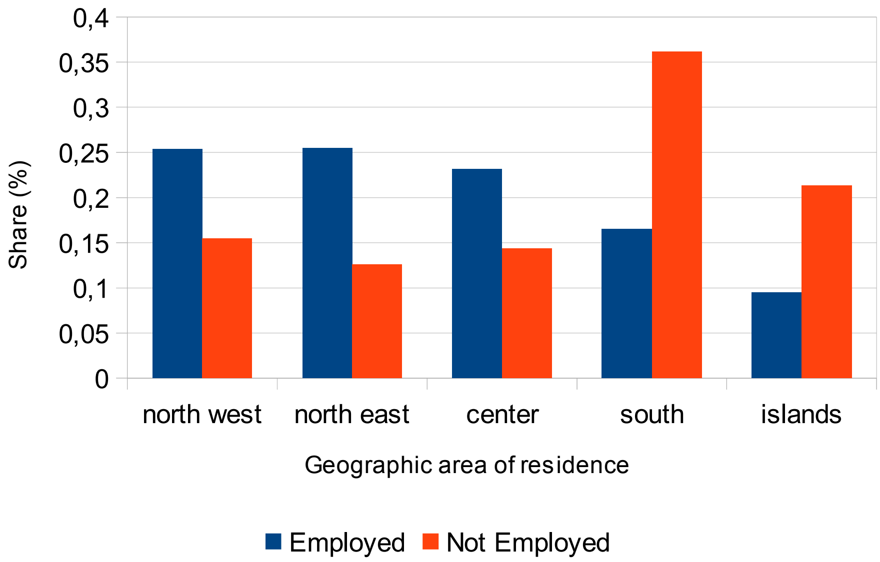
Some household-specific controls are also available:

- *Number of children in the age bands 0-3, 4-6, 7-14:* these are three continuous participation controls counting the number of individuals in the respective class *per household*[24]. The effect of these controls on participation might be mixed: on one side there is the need to stay at home due to caring commitments; on the other, the parent would need to work in order to economically provide for children. The former or the latter effects could prevail depending on the children's age.
- *Area of residence and size of the municipality*: both these factors might

23. Ignoring experience and including only the age control is also an option. In this case we would expect the estimated returns per year to capture part of the experience effect.
24. The variable is constructed in such a way that the woman in analysis does not necessarily have to be the mother of the children. She might also be an older sister still belonging to the household. Of course, in this second case (which does not involve many individuals given the way we constructed the sample) we do not expect the presence of kids to affect participation in the same way it would affect the mother.

affect the participation choice as well as the remuneration received. Cultural differences between north and south might be the reason of unequal labor market participation. In this regard, Figure 4.4 shows the share of women in/out employment (over the national total) by geographic area. Similarly, also the cost of living (including the price of labor services) might vary between areas[25].

Figure 4.4 – Share of women in and out employment by geographic area



Source: SHIW 2012

The data do not differ much between northern area (west and east) and central area. All three have between 23 and 25% of the nationwide employed female population, and around 12,5 – 15,5% of the housewives. Conversely, a huge difference arises with the southern area and the islands. In both cases the housewives population is (in relative terms) more than

25 See Cannari and Iuzzolino (2009)

twice as big as the working population. We expect the estimates to reflect these disparities. Conversely, regarding the size of the municipality (proxied by the number of inhabitants), we might expect residing in big metropolitan areas to be associated with higher wages.

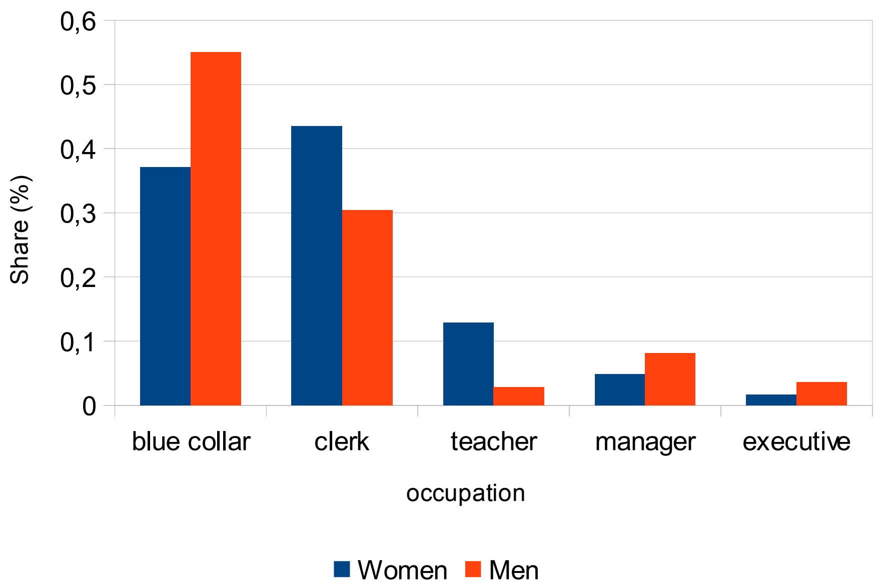
- *Percentage of income earners in the family*: is calculated as the ratio of total income earners in the household (excluding self) over total number of individuals, and is included in the selection equation as explanatory variable for the participation choice. We expect to observe higher probability of participation when the percentage is low, due to the need to economically provide for the family.

Finally, job-specific controls are included:

- *Occupation and sector:* the definition of occupation and sector of employment are fundamental for the purpose of measuring gender segregation. In turn, the impact of segregation on the pay differential is captured by the endowment effect ascribed to gender differences in the occupation and industry controls. Clearly, the way occupational and industry enter the wage equations can sensibly affect the estimates. One first option is that of including individual controls: the SHIW groups occupations in five classes (blue-collar, clerk, teacher, manager, executive/judge/university professor and similar) and occupations in 21 classes (see Figure 1 in the *Appendix*). Alternatively, we can use a continuous variable PF (percentage female) accounting for the share of women over the total *in the occupation*. This second method allows us to control for the *degree of "femaleness"* of an occupation. However, five classes are probably not enough to properly detect (and measure the impact of) segregation. A solution might be that of combining the data on the occupation with the industry of activity. If we want to create a *sector-*

occupation specific indicator, the variable PF would then assume up to 21x5=105 different values, which is a sensible improvement with respect to the previous 5. We will run multiple regressions in order to evaluate the different impact of the two specifications. Figure 4.5 reports the share of male and female population employed by occupation.

Figure 4.5 *– Share of total male and female population in employment by occupation*

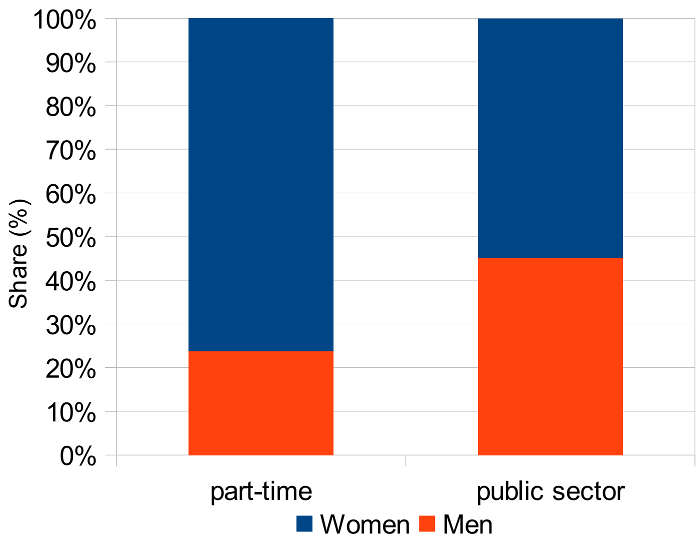


Source: SHIW 2012

Most of the population is employed either as blue collar or clerk (relatively more men than women for the former, vice-versa for the latter). The majority of teachers are women (12,8% against 2,8% of the employed population). As for managers and executives (and similar), we observe lower access to these occupations by women. See Figure 1 in <u>*Appendix*</u> for the distribution by sector.

- *Contract type:* the survey provides useful controls for contract type to be included in wage determination: temporary agency work (base), permanent and fixed term. Moreover, we will include a dummy for part-timers, since – as we saw – working shorter hours is much more common among women. Finally, we also add a dummy for public sector. Positions in public sector tend to provide women with better promotion prospects, more congenial hours and more equalized salaries than private employers do. The (relatively) better conditions attract women in higher number than men. Figure 4.6 shows the gender composition of the population in part-time employment and public sector.

Figure 4.6 *– Gender composition of the population in part-time status and in the public sector*



Source: SHIW 2012

Most of the population (in dependent work) having a part-time contract is female. As for public sector, genders are more or less equally represented, with a slightly higher presence of women.

- *Extra hours and income integration:* the yearly income reported in the survey includes compensations for over-time. By including a dummy for the presence of extra hours in the wage equation we can test both: (1) if overtime work is associated with significant hourly wage-premia, and (2) to which extent the returns differ by gender. Similarly, we also control for the presence of income integrations (like meal vouchers, company car etc.).
- *Company dimension:* the number of employees in the company is used as a proxy for the firm size. We will include this variable in the wage regression to test whether wages are higher or lower in big firms.

In addition to the charts presented, Table 1, 2 and 3 in the *Appendix* provide complete summary statistics (divided by gender and employment condition) for all the controls included in the estimations.

Chapter 5

Results

In this chapter we will present the results of our estimations. A number of regression have been run in order to test for the robustness of our findings. However, for reasons of space, we will only provide details about the two most significant specifications. Eventually, the results will be critically analyzed.

5.1 Results and comment

As we discussed in the previous chapters, the Oaxaca-Blinder decomposition involves first, the separate estimation of male and female wage equations, and second the division of the gap in endowment and coefficient effect. The controls included in the estimation of the wage equations are likely to affect significantly the size of the adjusted gap, hence we have to pay particular attention to them.

5.1.1 First specification: complete set of available controls

The first model in analysis includes most of the available controls. The age enters the wage and participation equations in classes (and *not* as continuous variable); (potential) labor market experience and its square are included, alongside with the number of job experiences; occupations and sectors of employment enter the wage equation via the linear variable “PF”.

The first four columns of Table 5.1 report the wage equations, with the estimated coefficients for the male and female samples (with relative p-value)[26]. The fifth and sixth columns contain the mean values of all the characteristics in analysis (by gender). The last two columns report the endowment effect (mean male minus mean female characteristics, weighted on men's returns) and the coefficient effect (men returns minus women returns, weighted on average female characteristics). In the last raw we reported the mean Inverse Mill's Ratio (IMR) and its relative coefficient.

In this first specification we simply included all the regressors that we had available and that we expected to be relevant in determining wage and participation choice. Some of the estimated coefficients might be not significant. However, even omitting these controls the results remain substantially unchanged (see Table 4 in the *Appendix*).

26. Remember that the women's equation is already corrected for the selection into employment.

Table 5.1 *– First specification, wage equations and gaps*

	Regressions				***Characteristics***		***Gap***	
	Men		***Women***		***Men***	***Women***	***Endowment effect***	***Coefficients effect***
	Coeff.	***P-value***	***Coeff.***	***P-value***	***Average***	***Average***		
Age (35to44)	-0,034	0,213	0,042	0,145	0,272	0,278	0,000	-0,021
Age (45to54)	0,048	0,180	0,039	0,282	0,348	0,360	-0,001	0,003
Age (55to64)	0,116	0,012	0,136	0,004	0,182	0,174	0,001	-0,004
Number of work experiences	-0,013	0,001	-0,026	0,000	2,263	2,067	-0,002	0,027
Experience	0,030	0,000	0,024	0,000	24,319	22,506	0,054	0,147
Exp squared	-0,001	0,000	0,000	0,000	719,204	635,614	-0,042	-0,050
Citizen	0,111	0,000	0,085	0,005	0,913	0,917	0,000	0,023
Elementary school	0,024	0,788	0,174	0,412	0,041	0,033	0,000	-0,005
Middle sc	0,129	0,120	0,175	0,401	0,346	0,212	0,017	-0,010
High sc (vocational)	0,141	0,100	0,231	0,272	0,092	0,090	0,000	-0,008
High sc	0,275	0,001	0,330	0,116	0,367	0,417	-0,014	-0,023
Bachelor	0,378	0,000	0,490	0,022	0,016	0,038	-0,009	-0,004
Master	0,545	0,000	0,551	0,009	0,115	0,195	-0,043	-0,001
Doctorate	0,645	0,000	0,579	0,009	0,017	0,014	0,002	0,001
North-east	0,024	0,229	0,015	0,490	0,221	0,255	-0,001	0,002
Center	-0,021	0,284	-0,033	0,139	0,206	0,232	0,001	0,003
South	-0,067	0,001	-0,066	0,013	0,224	0,165	-0,004	0,000
Islands	-0,082	0,000	-0,056	0,071	0,131	0,095	-0,003	-0,002
Municipality 20-40.000	0,011	0,572	-0,083	0,000	0,184	0,193	0,000	0,018
Mun 40-500.000	0,004	0,813	-0,054	0,005	0,483	0,478	0,000	0,028
Mun >500.000	-0,009	0,727	-0,062	0,063	0,082	0,076	0,000	0,004
PT	0,025	0,354	0,022	0,231	0,068	0,272	-0,005	0,001
Permanent contract	0,152	0,020	0,058	0,387	0,874	0,828	0,007	0,078

Fixed term	0,054	0,423	0,002	0,982	0,116	0,158	-0,002	0,008
Public sector	0,266	0,000	0,309	0,000	0,217	0,329	-0,030	-0,014
Extra hours	0,040	0,014	0,014	0,528	0,207	0,151	0,002	0,004
Income integ	0,030	0,122	0,017	0,539	0,140	0,096	0,001	0,001
PF	-0,092	0,005	0,090	0,044	0,350	0,565	0,020	-0,103
Company size 5 - 15	0,098	0,000	0,100	0,000	0,233	0,176	0,006	0,000
C.s. 16 - 19	0,117	0,001	0,135	0,002	0,051	0,037	0,002	-0,001
C.s. 20 - 49	0,144	0,000	0,190	0,000	0,098	0,074	0,004	-0,003
C.s. 50 - 99	0,159	0,000	0,156	0,000	0,058	0,046	0,002	0,000
C.s. 100 - 499	0,238	0,000	0,136	0,000	0,095	0,067	0,007	0,007
C.s. > 500	0,290	0,000	0,272	0,000	0,113	0,079	0,010	0,001
Constant	1,224	0,000	1,247	0,000				-0,023
Mill's			***0,037***	***0,128***		***0,319***		

Let's first analyze the findings variable by variable:

- The results regarding the returns on *age* are mixed. Sometimes women record higher (relative) returns, sometimes is the other way around. The net account seems to favor women.
- *Changing job* seems to damage both sexes (from a strictly pecuniary point of view). This is *not* in line with our expectations for the men sample (the negative sign is found also with other specifications), but it confirms our hypothesis for women.
- Returns to *experience* seem to be highly relevant in explaining the gap. First, women have (on average) two years of experience *less* than men. Second, lower returns are responsible for creating a 14,7% wage differential. However, part of this is mitigated by the slower rate of decrease in marginal returns of women[27].

27. Since our measure of experience might be imprecise, we ran another regression omitting all the experience controls (and all the insignificant regressors – see regression n.7, Table 4 in the Appendix). The test gives similar results: the contribution of experience is now captured by age (and its square, included in order to account for diminishing marginal returns), but the same kind

- *Educational attainments* and *returns to education* seem to favor women over men. As we saw before, employed women tend to leave school later. Moreover, women have higher returns than men for all the educational levels (apart from doctorate studies). We will provide a possible explanation for this is Section 5.2.
- Regarding the *contract type*, we see that having a permanent contract (rather than a temporary employment contract) grants a significant 15% percent hourly pay premium to men, but the figure is only 5% for women.
- As we expected, the dummy for *public sector* significantly reduces the pay gap: more women are employed in PA and they receive a relatively higher hourly pay.
- *Extra hours, income integrations* and *company size* are not that relevant in explaining the gap, although most of the figures seem to be (even slightly) in favor of men.
- The impact of *segregation* on the wage gap is measured by the endowment effect relative to the variable PF: $(\bar{PF}^m - \bar{PF}^f)\widehat{\beta_{PF}^m}$. The first term has to be negative (obviously we expect more women to be employed in female-dominated sectors/occupations). The second term is negative if returns are lower where more women are employed. This is indeed the case, so the overall sign is positive: *segregation does contribute to explaining the wage gap, and it is responsible for a 2% wage loss for women*. On the returns side the effect is mitigated by the fact that women are paid more than men in female-dominated positions. These two phenomena do not have to be confused: in the first case we are measuring the impact of lower payments in female-dominated positions *with respect to other positions.* In

of unequal returns arise.

the second case we are evaluating whether men are paid more or less than women *within female-dominated positions.*

- The coefficient of the Inverse Mill's Ratio (yet not completely significant) has the expected positive sign, which confirms the hypothesis that women in employment have higher salaries than those that housewives could have expected if they decided to work[28].

Table 5.2 summarizes the results of this first specification. Women are – on average – more endowed than men with characteristics rewarded in the labor market (-2,11%). However, the same characteristics generate higher returns for men (+8,39%). The correction term is negative (-1,19%), suggesting that if we did not control for selection, we would have largely underestimated the coefficient effect. We can interpret the wage gap due to returns (coefficient effect or adjusted pay gap) as discrimination. However, we have to bear in mind that: (1) this measure does not keep into account discrimination that might arise in "accessing the characteristics" (occupations and education in particular); (2) we don't know exactly which is the best set of controls (and whether we can have these controls available), so the magnitude of the net gap can be sensibly different.

28. Or, alternatively, the errors of the participation equation are correlated with those of the wage equation.

***Table 5.2** – First specification, results summary*

Log hourly wage (men)	*2,195*
Log hourly wage (women)	*2,144*
Wage gap due to characteristics (endowment effect)	*-2,11%*
Wage gap due to returns (coefficient effect)	*+8,39%*
Wage gap due to selection (Heckman correction)	*-1,19%*
Raw wage gap	*5,12%*

The access to the labor market is controlled by the participation equation. As before, we included here all the (relevant) available controls. Table 5.3 reports the estimates.

In interpreting the results it is important to bear in mind that given the nature of the samples in analysis, the choice we are hereby modeling is that of staying at home (*housewife)* or working (*dependent worker*). Let's analyze the marginal contribution of each variable in explaining participation:

- We can notice how being in the *age* interval 35-44 increases the chance of being employed (relatively to the interval 23-34). For the age 45-54 the estimated probability is the same. Conversely, it is sensibly lower for the oldest group (55-64)[29].
- Being *married* has a huge negative impact on the probability of participation, confirming the evidence that women are still way more affected than men by family choices. Conversely, *divorce* does not seem to be statistically significant.
- *Education* has the expected positive effect, increasing as we move up to higher attainments: investment in human capital tends to rise the expected wage and push women into employment.

29. We should take into account inter-generational differences in aptitudes towards female work. What we are comparing here is individuals belonging to different generations, hence we should expect to observe also different aptitudes towards work.

- Surprisingly, the *number of young kids* in the household does not have a significant effect on participation. However, as we move up in the age of the children, the effect tends to pass from negative to positive (as expected).
- The coefficient for *percentage of income earners* is unexpectedly positive, suggesting that in families with a lot of income earners it is also more likely for the woman to be in employment. This is due to the high permanence of sons and daughters in the household (even after the commencement of the working life) which is a typically Italian phenomenon.
- *Geographic area* is another significant factor: the probability of participation (relatively to the north-west area) is slightly lower in the center and much lower in the south and islands. Conversely, the *size of municipality* is not significant.

Most of the estimated coefficients for both, wage and selection equations, are in line with our expectations and with the literature (Zizza, 2013 in particular, since it is the only recent work employing SHIW data). Additional comments on the comparability with other studies will be provided further on.

***Table 5.3** – First specification, participation equation*

Variable	***Coefficient***	***P-value***	***Variable***	***Coefficient***	***P-value***
Age (35to44)	0,240	0,026	Number of child up to 3 yrs	-0,079	0,391
Age (45to54)	0,016	0,886	N. chil up to 6	0,004	0,969
Age (55to64)	-0,451	0,000	N. chil up to 14	0,076	0,131
Citizen	-0,084	0,411	% income earners	4,574	0,000
Married	-1,606	0,000	*North-east*	0,008	0,930
Divorced	0,183	0,193	*Center*	-0,148	0,101
Elementary school	-0,016	0,963	*South*	-0,680	0,000
Middle school	0,526	0,127	*Islands*	-0,629	0,000
Vocational high school	0,950	0,007	*Municipality 20-40.000*	0,031	0,715
High school	1,335	0,000	*Mun 40-500.000*	-0,014	0,841
Bachelor	1,924	0,000	*Mun >500.000*	0,051	0,659
Master	2,028	0,000	Constant	-0,088	0,809
Doctorate	7,574	0,000			

5.1.2 Second specification: Addabbo and Favaro (2007) model

The second specification that we will analyze here (Table 5.4) employs (where possible) the same controls used by Addabbo and Favaro (2007). The main differences with the previous model are: (1) no variable accounting for experience is included (hence we expect age to capture part of the experience returns); (2) occupation and sector of employment enter the wage equation as individual dummies. The choice might be particularly interesting because it allows us to test if our findings resemble Addabbo and Favaro's (2007), which is the only work in the literature employing exactly the same kind of correction we applied here.

***Table 5.4** – Second specification (Addabbo and Favaro, 2007), wage equations and gaps*

	Regressions				***Characteristics***		***Gap***	
	Men		***Women***		***Men***	***Women***	***Endowment effect***	***Coefficients effect***
	Coeff.	***P-value***	***Coeff.***	***P-value***	***Average***	***Average***		
Age (35to44)	0,112	0,000	0,147	0,000	0,272	0,278	-0,001	-0,010
Age (45to54)	0,221	0,000	0,163	0,000	0,348	0,361	-0,003	0,021
Age (55to64)	0,236	0,000	0,220	0,000	0,182	0,174	0,002	0,003
Elementary school	0,003	0,972	0,175	0,395	0,041	0,033	0,000	-0,006
Middle sc	0,141	0,083	0,158	0,438	0,346	0,212	0,019	-0,004
High sc (voc)	0,123	0,140	0,185	0,367	0,092	0,090	0,000	-0,006
High sc	0,188	0,021	0,212	0,302	0,367	0,417	-0,009	-0,010
Bachelor	0,205	0,032	0,315	0,134	0,016	0,038	-0,005	-0,004
Master	0,264	0,002	0,316	0,128	0,115	0,195	-0,021	-0,010
Doctorate	0,301	0,002	0,293	0,178	0,017	0,014	0,001	0,000
Public sector	0,183	0,000	0,228	0,000	0,217	0,329	-0,020	-0,015
Mining	0,255	0,000	-0,091	0,717	0,010	0,001	0,002	0,000
Manufacturing	0,164	0,000	-0,045	0,382	0,231	0,112	0,020	0,023
Supply 1	0,227	0,000	0,020	0,887	0,020	0,003	0,004	0,001
Supply 2	0,123	0,110	-0,074	0,721	0,008	0,001	0,001	0,000
Construction	0,195	0,000	0,037	0,736	0,095	0,006	0,017	0,001
Retail	0,102	0,008	-0,022	0,675	0,086	0,106	-0,002	0,013
Transport	0,096	0,021	-0,049	0,590	0,057	0,009	0,005	0,001
Catering etc	0,175	0,001	0,003	0,957	0,026	0,040	-0,002	0,007
ITC	0,061	0,297	0,010	0,900	0,017	0,013	0,000	0,001
Finance/insurance	0,226	0,000	0,116	0,064	0,037	0,040	-0,001	0,004
Real estate	0,138	0,205	-0,031	0,824	0,004	0,003	0,000	0,001
Professionals etc.	0,180	0,001	-0,043	0,549	0,022	0,019	0,001	0,004
Administrative activitie	0,098	0,186	-0,062	0,365	0,009	0,023	-0,001	0,004
PA and defense	0,179	0,000	-0,063	0,283	0,117	0,095	0,004	0,023

Education	0,101	0,096	-0,011	0,845	0,037	0,159	-0,012	0,018
Health etc.	0,178	0,000	-0,020	0,705	0,052	0,137	-0,015	0,027
Entertainment	0,073	0,450	-0,092	0,466	0,005	0,004	0,000	0,001
Other service	0,133	0,000	-0,060	0,235	0,116	0,143	-0,004	0,028
Domestic personnel	-0,037	0,628	-0,160	0,005	0,008	0,055	0,002	0,007
IO and NGO	-0,021	0,847	-0,060	0,670	0,004	0,003	0,000	0,000
Part Time	-0,005	0,849	0,039	0,033	0,068	0,272	0,001	-0,012
Permanent	0,139	0,028	0,107	0,100	0,874	0,828	0,006	0,027
Fixed term	0,022	0,734	0,040	0,545	0,116	0,158	-0,001	-0,003
Clerk	0,098	0,000	0,122	0,000	0,304	0,435	-0,013	-0,011
Teacher	0,474	0,000	0,395	0,000	0,028	0,129	-0,048	0,010
Manager	0,327	0,000	0,257	0,000	0,081	0,048	0,011	0,003
Executive etc.	0,545	0,000	0,588	0,000	0,037	0,017	0,011	-0,001
Firm size: 5 - 15	0,089	0,000	0,062	0,018	0,233	0,176	0,005	0,005
16 - 19	0,103	0,002	0,094	0,031	0,051	0,037	0,001	0,000
20 - 49	0,130	0,000	0,152	0,000	0,098	0,074	0,003	-0,002
50 - 99	0,150	0,000	0,122	0,002	0,058	0,046	0,002	0,001
100 - 499	0,213	0,000	0,120	0,001	0,095	0,067	0,006	0,006
> 500	0,236	0,000	0,199	0,000	0,113	0,079	0,008	0,003
North-east	0,029	0,129	0,021	0,320	0,221	0,255	-0,001	0,002
Center	-0,003	0,862	-0,009	0,686	0,206	0,231	0,000	0,001
South	-0,039	0,042	-0,063	0,016	0,224	0,165	-0,002	0,004
Islands	-0,062	0,006	-0,055	0,068	0,131	0,095	-0,002	-0,001
Constant	1,393	0,000	1,457	0,000				-0,064
Mill's			***0,025***	***0,389***		***0,459***		

Most of the results mirror our previous findings. The only sensible differences involve the estimated coefficients of the age classes, which are higher for both, men and women. As we said above this is due to the absence of any control for experience (even potential).

The impact of occupational and industry segregation can only be computed by summing up the endowment effect relative to – respectively – all the occupation *and* all the sector dummies. Surprisingly, occupational segregation negatively contribute to the GPG (-3,16%). Conversely, industry segregation is positive and equal to 1,75%. This means that women tend to be employed in occupations paying (relatively) high wages, but at the same time in sectors paying (relatively) low wages. However, in the previous model we observed that when we use the general indicator PF, the overall segregation contribution is indeed positive. How can we reconcile these two results? One possible explanation is that the individual indicators do *not* control for the degree of "femaleness" of the occupation/sector, hence each and every occupation/sector has the same weight, even if the density of female population is particularly high or particularly low. Alternatively, we can "borrow" an explanation from the foreign literature: working on Australian data, Coelli (2014) shows that the degree of aggregation with which occupations are defined inevitably influences the estimates on segregation. In particular, he found that shifting from a one-digit to a four-digit level of aggregation produces estimates of opposite sign. So women actually seem to be more likely to be in higher paying position when occupations are coarsely grouped. However, as we move to higher levels of dis-aggregation, it is more probable to find women in the low-paying end of the distribution *within* ability groups. This does not necessarily need to be the case also for Italy, but further investigations might be useful to clarify the question[30].

Table 5.5 summarizes the results for this second specification: the findings do not differ sensibly from the previous ones. As we said, the overall endowment effect is slightly augmented (negatively) by the addition of occupational controls. However, also the coefficient effect is higher (positively): discrimination seems to

30. Unfortunately, the SHIW is not sufficiently detailed in grouping occupations to allow us to carry out this kind of analysis.

be even more intense in this second case.

Table 5.5 *– Second specification (Addabbo and Favaro, 2007), results summary*

Log hourly wage (men)	*2,195*
Log hourly wage (women)	*2,144*
Wage gap due to characteristics (endowment effect)	*-3,16%*
Wage gap due to returns (coefficient effect)	*+9,47%*
Wage gap due to selection (Heckman correction)	*-1,19%*
Raw wage gap	*5,12%*

5.1.3 Comparison with the literature

As previously said, the comparison with other works is difficult due to different data sources, estimation technique, controls available and reference year. Among the most recent, Zizza (2013) studies SHIW data and finds a pay-penalty oscillating between 4,9% and 7,7% (period 1995-2008). Instead, when the two-step correction is applied, the adjusted penalty increases to 9,1-13,2%. However, Zizza measures the gap by means of the pooled OLS method, which does not allow to study rewards differentials characteristic by characteristic. Since Zizza's work is the only one employing recent SHIW data, we ran a wage regression using a similar specification in order to check if our findings are in line with hers[31]. Table 5.6 reports the results.

The gender dummy is associated with a wage loss of 10,4%, which is within the fluctuation band identified by Zizza (2013). This indicates a substantial stability of the gap between 2008 (the last year in Zizza's analysis) and 2012 (the wave analyzed here). Moreover, the Mill's coefficient has the expected positive

31. Zizza (2013) applies a double correction: she models the probability of being in employment *and* the probability of being an independent worker. We only applied the first correction.

sign, confirming once again that women in employment are more endowed with market-rewarded characteristics than women not in employment.

Table 5.6 *– Pooled OLS wage regression (Zizza, 2013)*

Variable	***Coefficient***	***P-value***
Woman	-0,104	0,000
Number work experiences	-0,024	0,000
Exp	0,033	0,000
Exp squared	0,000	0,000
Elementary school	0,142	0,101
Middle school	0,259	0,002
Vocational high school	0,340	0,000
High school	0,492	0,000
Bachelor	0,680	0,000
Master	0,807	0,000
Doctorate	0,898	0,000
Constant	1,337	0,000
Mill's	***0,018***	***0,39***

Addabbo and Favaro (2007) apply the Oaxaca-Blinder decomposition and find a 6,3% raw gap, which can be broken down in 18% coefficient effect, -9,1% endowment effect and -3,6% correction. Even using a similar specification (where possible), our estimates widely differ: the adjusted wage gap is more or less half of that estimated by Addabbo and Favaro (2007); the endowment effect doesn't go beyond 3,3% (even with other specifications, see Table 4 in the *Appendix*) and the correction term is more or less one third. Conversely, Centra-Cutillo's (2009) findings better resemble ours: the study employs ISFOL data (2007) and applies a double correction for participation and occupation choice. The endowment effect is approximately -2,1%, while the coefficient effect (including the correction) is equal to 10,8% (leading to a net raw gap of 8,7%).

With respect to these studies, our findings show a slightly lower raw gap, and lower coefficient and endowment effects. Since there are valid reasons to doubt the comparability of these works, we don't believe we should try to draw any conclusion regarding the *dynamic* of the adjusted gap in the last few years. Yet, our findings can be useful as a *photograph* of the current gender gap situation.

5.2 Critiques

This section is intended as a critique to the estimation technique and the data employed in this study. Part of the observations will be an extension of comments already included in the previous sections. In addition, we will provide some research proposals to be further investigated.

Starting with the data, a first problem might be the presence of measurement error in the calculation of hourly wages. As we said, this information is not available in the survey, hence it needs to be indirectly inferred from the annual income, months worked and number of hours per week reported by the interviewees. Nevertheless, the use of hourly wages is necessary since any other measure (weekly, monthly, annual) would be biased by the presence of individuals working shorter hours. As we have already said, this is more common among women and would lead to overestimation of the wage gap, unless some correction is applied.

Indirectly calculating hourly wages exposes us to high risk of measurement error, since the exact amount of annual income, the number of months worked and/or the number of hours worked per week might be inaccurately reported. The problem regards the data source, hence it cannot be overcome easily. One solution might be that of checking if the hourly salaries inferred from the SHIW are in alignment with other data sources. If this hypothesis is confirmed, then measurement error is not likely to be any more of a problem when employing these data than when employing other. However, this is only a loophole, but it doesn't really solve the issue. One little advantage is that the hourly wage is here used as dependent variable, hence it does not generate biases in the estimates as long as the deviations from the true value are not systematic.

This leads to another consideration. We are here focusing on *hourly* pay and *hourly* wage gaps, but doing so we risk to overlook other discriminatory phenomena. The report of the European Commission (2013a) commented the evolution of Gender Gap during the current economic crisis, and observed how – in tough times – part-time employment has been used as an alternative to lay-offs. In other words, employers, instead of firing people, were making them work shorter hours. In 2010, in Europe, the share of male involuntary part-timers over the total was as high as 38,1%, 5,8% more than in 2007. For women the figure was 24% with an increase of 3,8 points. However, in absolute values this corresponds to 7,3 millions women and 3,2 million men, with an upsurge of 1,3 million against “only” 773.000. Clearly the phenomenon has interested women more than men (although percentage variations seem to reveal the opposite). As for Italy, according to the Commission's data, the country is one of the European nations with the highest percentage of involuntary part-time over the total (in 2011 the figure was over 70% for men and over 50% for women), alongside with other Mediterranean countries (Spain, Cyprus and Greece). Although it is really difficult to prove, we might suspect that women have been hit by involuntary part-time more than men because of discriminatory behaviors.

Another potential problem of this database is the absence of a measure for actual labor market experience. Instead, we have included in the regressions the *potential* labor market experience. We expect the former to be sensibly lower than the latter. Estimates based on potential experience might be biased because women are likely to have more intermittent labor force participation than men (Grimshaw and Rubery, 2002). The international literature sometimes tackled this problem by including a control for children presence in the female wage equation, so to reflect the loss in experience due to interruptions for pregnancy leave. Another solution that our survey makes available, is the use of the number of years of contribution as a proxy for actual experience. Individuals in employment have on average 19,6 years of contribution, against 23,5 years of potential experience, and the correlation between the two measures is quite high (0,7). However, the proxy might be imprecise for other reasons: for example the university years might have been included in the account.

Moving to the estimation technique, one first problem may concern the choice of the correction applied. In this work we only included a correction for the in/out employment choice. The decision has been formulated as a binary choice between being a housewife or being a dependent worker. This is somehow incomplete, since one might also want to enter the labor market as self-employed. The model should then include three options: staying at home, being a dependent or being an independent worker.

As we saw, Zizza (2013) solved the issue by employing a two stage selection process: in the first stage she models the probability of working vs not working, in the second the probability of choosing self-employment vs dependent work. The exclusion restrictions for the latter are the self-employed status of (at least one of) the parents and the degree of risk aversion. Despite the analysis would definitely benefit from it, we couldn't replicate this kind of correction since the 2012 wave of the SHIW does not include a measure of risk aversion.

Another potential problem is the presence of unobserved heterogeneity. In particular we could speculate that there are relevant determinants of wage that we are omitting and might lead to biased estimates. The classic example of *ability* is particularly relevant in this context: ability cannot be observed, so it's usually left into the error term of the regression. However, it is reasonable to expect that highly "able" individuals will find it easier to get an education, and will invest more in schooling (thus educational attainment and ability are correlated). This might have an *indirect* effect on wages (through education) and a *direct* effect (ability affects productivity and in turn wages)[32]. If we run a simple OLS regression, the estimated returns from schooling will be biased upwards, since they include a portion of the ability returns. The problem goes one step further in our analysis: highly ability-endowed women will reasonably expect (relatively) high wages (due to schooling investments and high productivity). Conversely, lowly endowed women will be less likely to be payed above the reservation level and will stay at home. As for men, they will decide to work independently from their ability level. The returns from schooling of all the individuals in employment will be biased upward, but women's will be "more biased" due to their ability being systematically higher than that of housewives. This might explain why in our estimates women have always higher returns from schooling than men.

There is actually another potential source of endogeneity that we have only briefly commented in the previous chapters. Women's perception of labor market discrimination may adversely affect decisions to invest in education and training. Or, differently said, women might feel discouraged to stay in school long, because they predict that their efforts won't be fairly rewarded. This lowers their chances of getting a well paid job, and inevitably worsens the gap even further.

32. This second hypothesis is questioned by the signaling theory (Spence, 1973): education doesn't really enhance productivity, but it serves as a signal for high ability since highly "able" individuals find it easy to have good results at school and go on with studies.

The problem adds up to the question of pre-market discrimination by employers, in the form of barriers to accessing occupations, training programmes etc. Both the phenomena have the common consequence of lowering the level of women's characteristics rewarded in the labor market. This is captured by the endowment effect. If we commit the mistake of hastily focus only on the coefficient effect as measure of the discriminatory part of the gap, we might overlook other sources of discrimination that intervene at earlier stages of women's working and educational life.

Chapter 6
Conclusions

Italy is in a rather backward position among European and high-income countries in closing its overall Gender Gap. Within the fours pillars of gender equality considered by the World Economic Forum, Italian women do as good as (or sometimes even better than) their male counterparts in educational and health, but they still suffer huge disparities in the access to political life and treatment in the labor market (in particular participation, remuneration and advancement opportunities).

This last point might sound surprising, since Italy is recorded as one of the European countries having the lowest Gender Pay Gap (difference between the mean male and mean female hourly wage). The differential between men's and women's salary has been oscillating around 5-6% in the last few years, and is way below the EU average (16,5%). However, if Italy is among the best for pay gap, it is also between the worst for female labor force participation (45-47% of the women between 15 and 64), and has a high and increasing proportion of women in part-time employment (25% of the active female population in 2004, 32% in

2013) which contributes to widen the gap in annual earnings.

We can talk about discrimination in the labor market only when workers with the same productive capacities are treated differently on the basis of the demographic group to which they belong. Thus, in the case of Gender Pay Gap, we can't say how much of the differential is actually ascribable to gender discrimination unless we control for the productive characteristics of men and women. This is the – so called – "adjustment" process of the pay gap, which can be done in different ways. In this work we presented the pooled OLS estimation (which involves the inclusion of a gender dummy in a standard log wage regression *à la* Mincer), and the well known Oaxaca-Blinder decomposition (which develops in two stages: separate estimation of wage regressions for the male and female samples, and decomposition of the raw – "undjusted" – gap in discriminatory part and endowment part). In addition, in presence of low female participation in employment, the analysis would definitely benefit of a selection correction (we presented here the *Heckman selection correction*) for the in/out labor force choice.

The preceding literature employing either methods points out that the adjusted hourly gap can be almost twice as big as the unadjusted. If the latter never goes beyond 9% (depending on the data source, reference year etc.), the former usually oscillates between 10 and 15%. This means that, if no discrimination between men and women was present, *female wages would be higher than male wages because women are (on average) more endowed than men with characteristics typically rewarded by the labor market.*

Our estimation employs 2012 data from the Survey of Household Income and Wealth (SHIW) of the Bank of Italy. We apply the Oaxaca-Blinder decomposition with selection correction *à la* Heckman, and we find an adjusted hourly pay gap between 8,4 and 9,4% (depending on the variable set specification), despite the raw gap is as low as 5,1%. Segregation of women in low paying occupations and sectors is responsible for a 2% differential between men's and women's hourly remunerations, although the estimates are sensible to the specification employed.

To conclude, we would like to say a few words on the effects of the existence and persistence of gender discrimination in wages *on women's lives* and *on the society as a whole*.

Gender pay gaps have directly observable economic and psychological consequences on the every day life of a woman, that include less availability of economic resources, lower economic independence, dissatisfaction on the workplace, less sense of self-fulfillment etc. But there is more than that: in principle we could advance the hypothesis that wage gaps are also the cause, and not only the effect, of gender polarization in the distribution of family commitments in the household. In other words, if earnings were more equalized, we would expect to see – for example – more dads taking on paternity leaves instead of their spouses.

To this we should add the long term effects: pay gaps (alongside with the fewer hours worked and the intermittent careers of women) lead to huge differences in earnings throughout women's life, and this is likely to reflect on unequal pension entitlements (in Italy, for example, the pension gap is well above 30%[33]). Consequently, old women are often at risk of poverty or social exclusion, much more than old men are.

From a strictly economic point of view, the feeling of being unfairly treated can affect women's commitment and care on the workplace and lower their productivity. Moreover, discrimination can impact on women's decisions

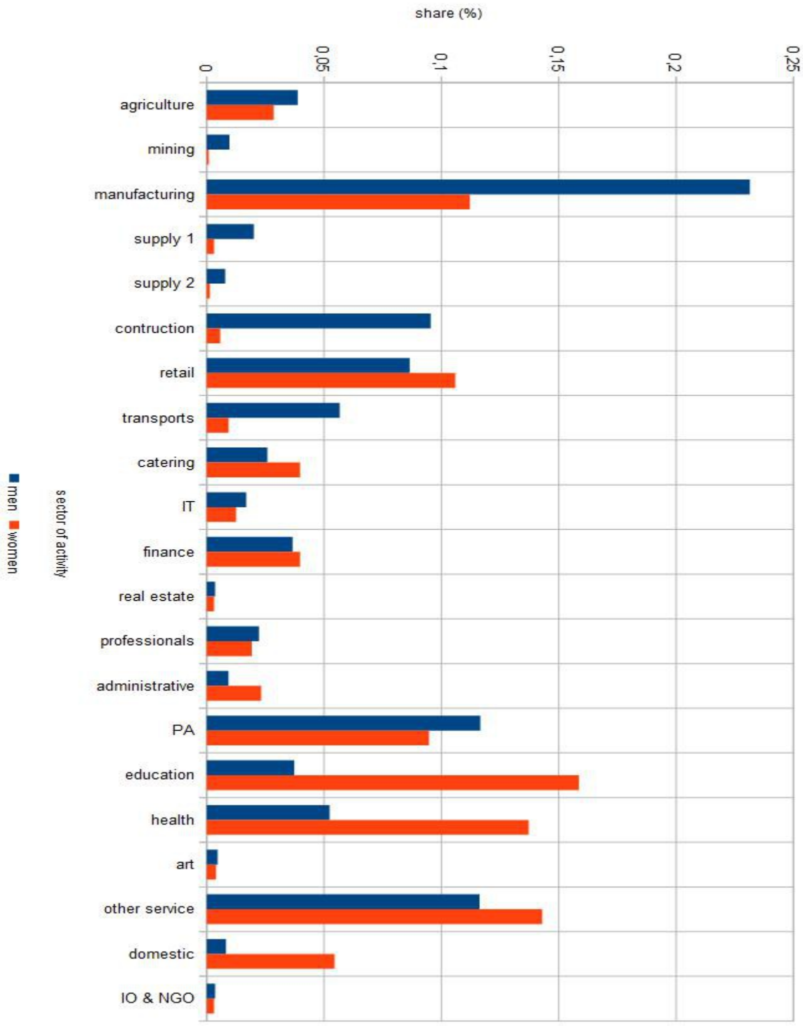
33. The European Commission issues a detailed report on the Gender Gap in Pensions across the EU countries. These data refer to the last edition (European Commission, 2013b).

regarding education and training investments, and in turn on their participation choice. All this translates into an enormous waste of human talent, which in the long run is a fundamental determinant of a country's competitiveness.

Every day, all over the globe, men have it easier than women in the work place (and not only). Closing the pay gap would have a number positive consequences on everybody's life, and should therefore be considered a priority and a moral imperative for modern societies.

Appendix

Figure 1



Sensible differences in gender participation arise in the manufacturing, construction and transports sectors, where men are employed in vast majority. Conversely health care and education are mainly female dominated sectors.

It is reasonable to expect some occupations to be sector-specific. In order to spot this association in our data we would need a higher level of dis-aggregation of occupations (at least 2 or 3 digits), which is not available for the SHIW database. However, even at this level of dis-aggregation we notice how the findings regarding the education sector closely resemble those of teachers in the distribution per occupation.

Table 1 – Summary statistics, men sample

Variable	Obs	Mean	Std. Dv.	Min	Max
Log hourly wage	2787	2,1956	0,4231	-0,0392	4,3428
Age	2787	44,36	10,27	23,00	64,00
Number of work experiences	2787	2,26	1,85	1,00	36,00
Experience	2787	24,32	11,31	0,00	52,00
Tenure	1484	12,75	9,86	0,00	43,00
Citizen	2787	0,91	0,28	0,00	1,00
Married	2787	0,68	0,47	0,00	1,00
Divorced	2787	0,04	0,20	0,00	1,00
Highest education attainment (base: no education)					
Elementary school	2787	0,04	0,20	0,00	1,00
Middle	2787	0,35	0,48	0,00	1,00
High school (vocational)	2787	0,09	0,29	0,00	1,00
High school	2787	0,37	0,48	0,00	1,00
Bachelor Degree	2787	0,02	0,12	0,00	1,00
Master Degree	2787	0,12	0,32	0,00	1,00
Doctorate studies	2787	0,02	0,13	0,00	1,00
Number of children up to 3 yr old	2787	0,11	0,35	0,00	3,00
Number of children up to 6 yr old	2787	0,10	0,32	0,00	2,00
Number of children up to 14 yr old	2787	0,31	0,62	0,00	3,00
Percentage of earners in the household	2787	0,27	0,23	0,00	0,83
Area (base: North-west)					
North-east	2787	0,22	0,42	0,00	1,00
Center	2787	0,21	0,40	0,00	1,00
South	2787	0,22	0,42	0,00	1,00
Islands	2787	0,13	0,34	0,00	1,00
Municipality size (base: up to 20000)					
20000-40000	2787	0,18	0,39	0,00	1,00
40000-500000	2787	0,48	0,50	0,00	1,00
>500000	2787	0,08	0,27	0,00	1,00
Part timer	2787	0,07	0,25	0,00	1,00
Contract (base: temporary)					

Permanent	2787	0,87	0,33	0,00	1,00
Fixed term	2787	0,12	0,32	0,00	1,00
Public sector	2787	0,22	0,41	0,00	1,00
Working extra hours	2787	0,21	0,41	0,00	1,00
Receiving income integrations	2787	0,14	0,35	0,00	1,00
Occupation (base: blue collar)					
Clerk	2787	0,30	0,46	0,00	1,00
Teacher	2787	0,03	0,17	0,00	1,00
Manager	2787	0,08	0,27	0,00	1,00
Executive, Judge, University professor etc.	2787	0,04	0,19	0,00	1,00
Sector of activity (base: agriculture)					
Mining	2787	0,01	0,10	0,00	1,00
Manufacturing	2787	0,23	0,42	0,00	1,00
Supply of electricity, gas, steam and air conditioning	2787	0,02	0,14	0,00	1,00
Supply of water, sewerage, waste treatment	2787	0,01	0,09	0,00	1,00
Construction sector	2787	0,10	0,29	0,00	1,00
Retail	2787	0,09	0,28	0,00	1,00
Transports	2787	0,06	0,23	0,00	1,00
Catering and accommodation	2787	0,03	0,16	0,00	1,00
Information technology and communication	2787	0,02	0,13	0,00	1,00
Financial and insurance activities	2787	0,04	0,19	0,00	1,00
Real estate	2787	0,00	0,06	0,00	1,00
Professional, technical and scientific activities	2787	0,02	0,15	0,00	1,00
Administrative and support service activities	2787	0,01	0,10	0,00	1,00
Public administration and defense	2787	0,12	0,32	0,00	1,00
Education sector	2787	0,04	0,19	0,00	1,00
Health and social care	2787	0,05	0,22	0,00	1,00
Artistic activities and entertainment	2787	0,00	0,07	0,00	1,00
Other service activities	2787	0,12	0,32	0,00	1,00
Domestic personnel	2787	0,01	0,09	0,00	1,00
International organizations and NGO	2787	0,00	0,06	0,00	1,00
Percentage of women per sector & occupation	2787	0,35	0,22	0,00	0,87
Percentage of women per occupation	2787	0,41	0,11	0,27	0,78
Company size (base: up to 5)					
5 - 15	2787	0,23	0,42	0,00	1,00

16 - 19	2787	0,05	0,22	0,00	1,00
20 - 49	2787	0,10	0,30	0,00	1,00
50 - 99	2787	0,06	0,23	0,00	1,00
100 - 499	2787	0,10	0,29	0,00	1,00
> 500	2787	0,11	0,32	0,00	1,00

Table 2 – Summary statistics, employed women sample

Variable	**Obs**	**Mean**	**Std. Dv.**	**Min**	**Max**
Log hourly wage	2238	2,1444	0,4392	-0,8755	4,6894
Age	2238	44,39	9,97	23,00	64,00
Number of work experiences	2238	2,07	1,56	0,00	15,00
Experience	2237	22,51	11,37	0,00	51,00
Tenure	1099	11,25	9,41	0,00	44,00
Citizen	2238	0,92	0,28	0,00	1,00
Married	2238	0,62	0,49	0,00	1,00
Divorced	2238	0,11	0,31	0,00	1,00
Highest education attainment (base: no education)					
Elementary school	2238	0,03	0,18	0,00	1,00
Middle	2238	0,21	0,41	0,00	1,00
High school (vocational)	2238	0,09	0,29	0,00	1,00
High school	2238	0,42	0,49	0,00	1,00
Bachelor Degree	2238	0,04	0,19	0,00	1,00
Master Degree	2238	0,19	0,40	0,00	1,00
Doctorate studies	2238	0,01	0,12	0,00	1,00
Number of children up to 3 yr old	2238	0,08	0,31	0,00	3,00
Number of children up to 6 yr old	2238	0,08	0,29	0,00	3,00
Number of children up to 14 yr old	2238	0,26	0,57	0,00	3,00
Percentage of earners in the household	2238	0,34	0,21	0,00	0,83
Area (base: North-west)					
North-east	2238	0,25	0,44	0,00	1,00
Center	2238	0,23	0,42	0,00	1,00
South	2238	0,17	0,37	0,00	1,00
Islands	2238	0,09	0,29	0,00	1,00
Municipality size (base: up to 20000)					
20000-40000	2238	0,19	0,39	0,00	1,00
40000-500000	2238	0,48	0,50	0,00	1,00
>500000	2238	0,08	0,27	0,00	1,00
Part timer	2238	0,27	0,45	0,00	1,00
Contract (base: temporary)					

Permanent	2238	0,83	0,38	0,00	1,00
Fixed term	2238	0,16	0,36	0,00	1,00
Public sector	2238	0,33	0,47	0,00	1,00
Working extra hours	2238	0,15	0,36	0,00	1,00
Receiving income integrations	2238	0,10	0,29	0,00	1,00
Occupation (base: blue collar)					
Clerk	2238	0,44	0,50	0,00	1,00
Teacher	2238	0,13	0,33	0,00	1,00
Manager	2238	0,05	0,21	0,00	1,00
Executive, Judge, University prossor etc.	2238	0,02	0,13	0,00	1,00
Sector of activity (base: agriculture)					
Mining	2238	0,00	0,03	0,00	1,00
Manufacturing	2238	0,11	0,32	0,00	1,00
Supply of elecity, gas, steam and air conditioning	2238	0,00	0,06	0,00	1,00
Supply of water, sewerage, waste treatment	2238	0,00	0,04	0,00	1,00
Construction sector	2238	0,01	0,08	0,00	1,00
Retail	2238	0,11	0,31	0,00	1,00
Transports	2238	0,01	0,10	0,00	1,00
Catering and accomodation	2238	0,04	0,20	0,00	1,00
Information technology and communication	2238	0,01	0,11	0,00	1,00
Financial and insurance activities	2238	0,04	0,20	0,00	1,00
Real estate	2238	0,00	0,06	0,00	1,00
Professional, technical and scientific activities	2238	0,02	0,14	0,00	1,00
Administrative and support service activities	2238	0,02	0,15	0,00	1,00
Public administration and defense	2238	0,09	0,29	0,00	1,00
Education sector	2238	0,16	0,37	0,00	1,00
Health and social care	2238	0,14	0,34	0,00	1,00
Artistic activities and entertainment	2238	0,00	0,06	0,00	1,00
Other service activities	2238	0,14	0,35	0,00	1,00
Domestic personnel	2238	0,05	0,23	0,00	1,00
International organizations and NGO	2238	0,00	0,06	0,00	1,00
Percentage of women per sector & occupation	2238	0,57	0,19	0,02	1,00
Percentage of women per occupation	2238	0,48	0,15	0,27	0,78
Company size (base: up to 5)					
5 - 15	2238	0,18	0,38	0,00	1,00

16 - 19	2238	0,04	0,19	0,00	1,00
20 - 49	2238	0,07	0,26	0,00	1,00
50 - 99	2238	0,05	0,21	0,00	1,00
100 - 499	2238	0,07	0,25	0,00	1,00
> 500	2238	0,08	0,27	0,00	1,00

Table 3 – Summary statistics, housewives (only relevant variables)

Variable	Obs	Mean	Std. Dv.	Min	Max
Age	1674	49,39	9,80	23,00	64,00
Citizen	1674	0,93	0,26	0,00	1,00
Married	1674	0,93	0,26	0,00	1,00
Divorced	1674	0,02	0,15	0,00	1,00
Highest education attainment (base: no education)					
Elementary school	1674	0,20	0,40	0,00	1,00
Middle	1674	0,44	0,50	0,00	1,00
High school (vocational)	1674	0,07	0,25	0,00	1,00
High school	1674	0,23	0,42	0,00	1,00
Bachelor Degree	1674	0,01	0,08	0,00	1,00
Master Degree	1674	0,03	0,17	0,00	1,00
Doctorate studies	1674	0,00	0,00	0,00	0,00
Number of children up to 3 yr old	1674	0,09	0,33	0,00	3,00
Number of children up to 6 yr old	1674	0,10	0,32	0,00	2,00
Number of children up to 14 yr old	1674	0,31	0,62	0,00	3,00
Percentage of earners in the household	1674	0,10	0,17	0,00	0,75
Area (base: North-west)					
North-east	1674	0,13	0,33	0,00	1,00
Center	1674	0,14	0,35	0,00	1,00
South	1674	0,36	0,48	0,00	1,00
Islands	1674	0,21	0,41	0,00	1,00
Municipality size (base: up to 20000)					
20000-40000	1674	0,19	0,39	0,00	1,00
40000-500000	1674	0,50	0,50	0,00	1,00
>500000	1674	0,10	0,30	0,00	1,00

Table 4 – Results summary for all the specifications analyzed

In what follows we report a summary of all the specifications tested. Every model includes different controls (both in the wage and in the participation equations). The last raws of the table report the estimated coefficient effect, endowment effect, correction, raw gap and segregation contribution to the wage gap. Follows a brief description of the specifications:

- *Number 1* includes all the available variables. We considered linear indicators for age and experience, and the variable PF for occupation and industry of employment.
- *Number 2* is the same as n.1, apart from the age that enters both the equations in classes – *specification commented in the results chapter.*
- *Number 3* is the same as n.2, apart from the indicator PF which is constructed by occupation (and not by occupation and sector).
- *Number 4* is again the same as n.2, but we omit the variable PF and we consider individual indicators for occupation and industry.
- *Number 5* is the same as n.4, but experience enters the wage equation in classes.
- *Number 6* use the same specification as Addabbo and Favaro (2007), where possible – *specification commented in the results chapter.*
- *Number 7* is the same as n.1, but all the insignificant variables and all the proxies for experience are excluded (we saw that they might be unreliable measures of the actual experience). Instead, age and squared age are included.
- *Number 8* is the same as n.2, but once again all the proxies for experience are omitted.

Specification code	**1**		**2**		**3**		**4**		**5**		**6**		**7**		**8**	
Regression	**W**	**P**	**W**	**P**	**W**	**P**	**W**	**P**	**W**	**P**	**W**	**P**	**W**	**P**	**W**	**P**
Age	x	x											x	x		
Age class (base: up to 34)			x	x	x	x	x	x	x	x	x	x			x	x
35 to 44																
45 to 54																
55 to 64																
Number of work experiences	x		x		x		x		x				x			
Experience (potential)	x		x		x		x									
Experience squared	x		x		x		x									
Experience class (base: 0 to 5)									x							
6 to 10																
11 to 20																
20																
Tenure																
Citizenship (D)	x	x	x	x	x	x	x	x	x	x			x		x	x
Married (D)		x		x		x		x		x		x		x		x
Divorced (D)		x		x		x		x		x				x		x
Education level (base: no education)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Elementary																
Middle																
Vocational highschool																
Highschool																
Bachelor																
Master																
Post																
Number of children in		x		x		x		x		x		x		x		x

age band																
Up to 3																
Up to 6																
Up to 14																
Percentage of income earners in the family		x		x		x		x		x				x		x
Area (base: North-west)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
North-east																
Center																
South																
Islands																
Municipality (base: small – up to 20,000)	x	x	x	x	x	x	x	x	x	x			x		x	x
Medium																
Big																
Huge																
Part-time (D)	x		x		x		x		x		x				x	
Contract type (base: temporary)	x		x		x		x		x		x		x		x	
Permanent																
Fixed term																
Public sector (D)	x		x		x		x		x		x		x		x	
Extra hours (D)	x		x		x		x		x				x		x	
Income support (D)	x		x		x		x		x						x	
Occupation (base: blue collar)							x		x		x					
Clerical																
Teacher																
Manager																
Executive, university professor, judge etc.																
Sector (base: agriculture)							x		x		x					

Extractive																
Manufactures																
Supply 1 (electricity etc.)																
Supply 2 (water, drainage etc.)																
Building																
Retail, mechanic																
Transportation and storage																
Reception																
IT service																
Finance and insurance																
Real estate																
Scientific																
Administrative																
Public sector and defense																
Education																
Healthcare																
Arts and entertainment																
Other services																
Family service, housekeeping etc.																
International organizations																
Percentage Female (per sector and occupation)	x		x										x		x	
Percentage Female (per occupation)					x											
Firm dimension (base: up to 4 employees)	x		x		x		x		x		x		x		x	
5 to 15																
16 to 19																

	20 to 49								
	50 to 99								
	100 to 499								
	More than 500								
Endowment effect		-2,50%	-2,11%	-3,28%	-3,00%	-3,09%	-3,16%	-2,48%	-2,17%
Coefficients effect		8,41%	8,39%	9,46%	9,01%	9,24%	9,47%	8,73%	8,65%
Correction term		-0,82%	-1,19%	-1,08%	0,92%	1,03%	-1,19%	-1,11%	-1,36%
Raw gap		5,11%	5,09%	5,09%	5,08%	5,12%	5,12%	5,13%	5,12%
Segregation		2,09%	1,98%	0,49%	-3,58% (by occ) 1,29% (by sec)	-3,69% (by occ) 1,46% (by sec)	-3,89% (by occ) 1,75% (by sec)	2,38%	2,28%

As we can notice, the endowment effect oscillates between -2,11% and -3,28%. The two extreme values are recorded for the second and third specifications, whose only difference is the way we construct the PF indicator. In turn, this should also affect segregation, which is indeed much lower in specification n.3 (only 0,5%). The reason why this happens is that – as I've already observed – segregation is stronger at industry level than it is at occupational level. Hence, only the PF indicator used in specification n.2 can entirely capture the phenomenon.

The coefficient effect varies between 8,39% and 9,47%. Once again we observe a wide gap between specifications 2 and 3, but this is due to discrimination capturing now the portion of gap that was previously explained by the endowment effect.

The correction term oscillates slightly above and below 1%, and the raw wage gap is equal to 5,1% (little variations are due to rounding).

As long as the indicator PF is constructed by sector *and* occupation, the estimated contribution of segregation in explaining pay gaps is around 2% (first and last two specifications). If we enter individual indicators instead, the evidence is mixed. As we said before, this might be due to the dummies not capturing the degree of "fameleness" of each occupation and industry of employment.

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