A Counterfactual analysis of the gender wage gap: A new micro-evidence from the Tunisian labor market.

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Abstract

This study aims to measure the gender wage gap in the Tunisian labor market. Our investigation essentially extends the traditional Oaxaca-Blinder decomposition technique (1973). It also proposes a counterfactual analysis along the entire wage distribution. The fundamental basis of this method is to set up a counterfactual distribution that allows us to estimate the male-female wage gap at each quantile. As shown in our empirical analysis, the gender pay gap does not refer to the differences in observable characteristics between males and females. It is rather the outcome of discriminatory practices against women.

JEL classification: …

***Keywords*:** composition effect, counterfactual analysis, counterfactual distribution, discriminatory practices, gender wage gap, Oaxaca-Blinder decomposition, quantile, structure effect.

1. Introduction

The wage disparity between men and women has been an active research area in the past few decades. Becker's (1957) human capital theory is the first approach that aims at measuring gender wage differentials. It defines wages as remuneration schemes to enhance productivity. In this context, the wage gap between males and females refers to differences in productivity. In a discriminatory environment, the gender earnings gap persists even if the males and females' labor market characteristics remain the same. Gender discrimination takes place when male and female workers with comparative labor productivity levels receive different earnings. In this respect, Blau and Khan (2000) claim that gender wage gap is an obvious fact, even after controlling for such factors as the productivity of males and females.

In recent years, another approach has been suggested, it argued that employers' discriminatory practices against females are not the major cause of gender wage inequality. The division of household chores between husbands and wives could be a main factor explaining this inequality. With the birth of a new child, men focus on paid work while women concentrated on childcare and household. This division of labor means that females, compared with men, are more likely to encounter job interruptions, gain less work experience, and thus choose part-time jobs.

Labor economic studies put a special focus on how to measure the gender wage gap is due to either the employers' discriminatory actions or private family decisions.

The Oaxaca-Blinder decomposition method (1973) has dominated the econometrics literature in general, and discrimination studies in particular. The major purpose of this method is to decompose the wage disparity into two parts. The first part corresponds to the wage differential ascribed to differences in discernible characteristics. The second part stands for the male-female wage gap due to differences between feature coefficients as gender wage discrimination. According to this method, the second part is unexplained, it corresponds to the difference between the average remuneration for men and women's salaries with the same characteristics as men.

It should be mentioned that the basis of the Oaxaca-Blinder decomposition technique (1973) is to examine overall average effects. Nevertheless, the analysis of the average male-female wage differential is restricted. One of the limitations of this Oaxaca method is its inability to show how the gender wage gap changes depending on wage distributions. This might lead us to assume that both pay differential and observable covariates are constant across the entire wage distribution.

In order to investigate how the two components of the Oaxaca-Blinder decomposition technique are dispersed along the wage distribution (Anja Heinze, 2006), we decompose and calculate the gender pay gap at each quantile of the wage distribution.

Motivated by the uncontrolled spread of gender wage inequality, our paper aims to extend the Oaxaca-Blinder decomposition by carrying out a counterfactual analysis, which will be explained subsequently.

The contribution of this paper is threefold. First, we will provide an overview of the literature on gender pay discrimination by developing the newly discussed interpretations of gender disparities. Second, we will represent the Oaxaca-Blinder decomposition technique and show how this method restricts the analysis to only measuring the average of wage gap. We will eventually decompose the male-female wage gap into a composition effect related to differences in terms of employment characteristics and structural effects. We will use this counterfactual decomposition by creating a counterfactual distribution to assess the extent of the gender pay gap across the entire wage distribution. The versatility of this method lies in the prevention of the selection bias based on observable characteristics. To the best of our knowledge, this study is the first to estimate the gender wage gap using counterfactual analysis in Tunisia.

The remainder of this paper is organized as follows. Section 2 enumerates the various theories of gender wage discrimination. Section 3 sheds light on the situation of females in the Tunisian labor market. In section 4, we represent the Oaxaca-Blinder method used for decomposing the wage gap. Section 5 focuses on the counterfactual analysis. We finally draw some conclusions in section 6.

2. Literature review on gender wage discrimination

Edgeworth's (1922) theory reduces economic discrimination in one form, namely the wage discrimination between two individuals with comparable economic characteristics. Stiglitz (1973) elucidated that wage disparities are systematically correlated with non-economic aspects, such as religion and race.

Discrimination has been the subject of extensive applied research and comparative economic studies, which permit to measure its evolution but leave extensive areas of uncertainty to its causes and dynamics. The human capital theory explains the differences noted between men and women in the labor market with major discrepancies in human capital investment.

In the wake of human capital theory, approaches based on individuals' labor market preferences have been advanced to account for occupational and wage discrepancies between men and women (Daymont and Andrisani, 1984; Filer, 1986).

Similar to the very first discrimination studies, gender wage inequality refers to differences in training and labor market experience (Becker 1985). However, in recent decades, the educational levels of men and women steadily converged. In most countries, young women's attainment of university degrees outpaced men's.

Less differences in education and professional experience have been detected, compared to wage differences between the two sexes. This can be explained by the fact that there must be other factors that could be seen as potential causes of growing income inequality.

Discrimination theories analyze differences between individuals with identical productive capacities. Therefore, discrimination occurs when people of equal capacity and qualification are treated differently according to their gender (Blau and Ferber, 1992). Becker's (1964) work on human capital and discrimination provides a limited tool in analyzing income inequality because it does not consider sexism in the labor market.

Employers' discriminatory actions represent another potential cause of women's lower incomes. In Switzerland, over 80% of women reduce their working hours after the birth of their first child or even withdraw from the labor market (Giudici and Schumacher 2017). Employers may systematically expect all women to do the same and therefore be less willing to invest in the careers of their female employees from the outset.

Based on the demand theory, segregation can be explained by referring not only to the differences in human capital investments, but also to the discrimination that criminalizes employers' attitudes towards women. Furthermore, the transaction cost theory identifies imperfect information available to employers, giving rise to discriminatory attitudes. Moreover, the Institutional theory emphasizes the social constraints and traditions that influence individual choices. All these theories offer diverse explanations of gender inequality. However, they do not analyze its foundations in the labor market in a coherent and accurate way.

Economists often justify this unexplained wage gap based on maternity and labor choices. (Becker 1985, Polachek 2006). Fathers focus on jobs, while mothers concentrate on childcare and households. The disparity in the professional preferences of women and men thus increases. Hence, gender pay inequality is explained by the decisions made within households instead of the employers' discriminatory behaviors.

Women narrow their professional opportunities in the labor market by focusing on household activities rather than a professional life (Havet, 2004). These choices reduce human capital accumulation, leading to significant differences in the attribution of jobs and wages (Ponthieux and Meurs, 2004). As for Polachek (1981), these individual preferences reflect the women's role in biological reproduction and their low attachment to the labor market. The situation of women would, therefore, depends on the levels of human capital. However, this theory can be challenged by improving women's qualifications and professional experience. Gender inequalities persist even with equal qualifications. This approach shows that females' preference not to participate in the labor market is a fundamental argument of gender wage discrimination.

Goldin (2014) considers employment discrimination against women as the upshot of the need to defend male professional positions and sustain their profits. Thus, a woman's entry into a male-dominated job deteriorates the prestige of the profession even if she possesses the qualifications required to perform the job. Goldin (2014) bases his explanation on the imperfection of information within the company. Since they do not recognize the candidate's actual skills, men will interpret females' presence as a sign of devaluation of their work. Women are more risk-averse compared to men. Thus, they opt for less risky careers (Croson and Gneezy, 2009; Charness and Gneezy, 2012).

Females are reportedly more reluctant than males to engage in wage negotiations and promotion requests (Babcock et al., 2003), which may explain both the income gap and the status gap between men and women. These conclusions should be considered with caution due to the limited explanatory scope of wage differentials (Manning and Farzad, 2010).

As a starting point for the decomposition of wage gaps, Oaxaca technique becomes one of the most privileged ways of studying gender wage gaps. The fundamental idea is to divide the gender wage gap into an explained part, including productivity differences**,** and another part emanating from different remunerations with identical characteristics. It should be noted that the second part deals with gender discrimination.

3. Labor market characteristics of Tunisian women

The overall female unemployment rate in the North African region is 15.3%, compared to a worldwide average of only 6.5%. The International Labour Organization (ILO) states that the high proportion of jobless people, especially immature women, represents only the tip of the iceberg. Females' jobs are mostly unpaid and precarious. Due to their substandard quality, these jobs do not comply with labor standards or workers' rights.

	2011	2012	2013	2014	2015	2016	2017	2018
Male	72.70%	72.83%	72.21%	71.87%	71.70%	71.26%	71.23%	71.11%
Female	27.30%	27.17%	27.79%	28.13%	28.30%	28.74%	28.77%	28.89%

Table. 1–Labor force according to gender in (%)
Source: INS.

According to the latest employment survey provided by the INS[1], the Tunisian female labor force reached 28.9% out of the total labor force. The female workforce is a function of the female activity rate, estimated at 24.9% compared to 70.1% for males. However, the female activity rate is below its actual level in case of disruptions in both economic and political conjuncture in the past few years.

With their growing demand for work, over 43,000 female higher education graduates each year, including at least 27,000 seeking their first job. Meanwhile, the total working population decreased from 3277.4 thousand to 3139.8 thousand in May 2010. Female employment was heavily affected by the economic situation after the Tunisian revolution. (-73.9 job loss in thousands).

Female unemployment exploded. The corresponding rate rose from 15.2% in 2005 to 28.2% in 2011. With slight ups and downs, the female unemployment rate reached 22.9% in 2018. Meanwhile, the male unemployment rate slowly increased from 12.1% in 2005 to 15.4% in 2011. Since 2015, it has stagnated at about 12.5%, as shown in the table below, compared to the overall unemployment rates. Despite its slightly positive fluctuations throughout the past years, the unemployment rate was still high.

	2011	2012	2013	2014	2015	2016	2017	2018
Total	18.9	16.7	15.3	15.0	15.4	15.5	15.5	15.5
Male	15.4	13.9	12.8	12.5	12.5	12.5	12.5	12.5
Female	28.2	24.2	21.9	21.1	22.6	23.1	22.9	22.9

Table.2–Unemployment rate according to gender in (%)
Source: INS

Recent data on female unemployment show that employment promotion programs have reached a certain limit. Admittedly, Tunisian women do not encounter any real regulatory obstacles to employment or business creation, but social and cultural retentions continue to work to their disadvantage. The unemployment that hits women with higher educational levels is an essential revealing factor in this respect.

The Tunisian political and economic situation has dramatic direct effects on employment in general and female employment in particular. Both the sharp decline in economic activity and the slowdown in investment, notably in labor-intensive sectors, led to an explosion of employment demand and a progressive increase of the unemployment rate. The situation would be more unfavorable to women, since females' demands for jobs become higher than that of men, and job supply is still limited.

[1] INS, Institut National de la Statistique.

Tunisian women have entered the labor market on a massive scale since the 1990s. Meanwhile, their educational levels and qualifications have increased. However, their employment rate is still farther compared to that of men. A survey conducted in 2004 on the determinants of university graduates' salaries revealed that men are better paid than women regardless of the level of the qualification. The majority of women work in low-paying sectors, although they represent 61.5% of the workforce.

Tunisian women are part-time workers, who suffer from underemployment and precariousness, and mismatches between their qualifications and jobs. Employment plays a pivotal role in our society. It guarantees autonomy and financial independence. Work is the best form of rewarding women's education. In fact, jobs and wages represent a fair return on investment in human capital. Unfortunately, women's status in the labor market is not idyllic yet.

4. Econometrics foundations and estimation results of the gender gap decomposition

4.1. Oaxaca- Blinder" decomposition technique

Following "Oaxaca- Blinder" decomposition technique (1973), an earnings equation, relating wages to the employees' attributes is estimated separately for males and females. Let W be the logarithm of salaries in which we observe a set of K individual determinants. The observable characteristics could correspond to education, labor market experience, etc.… A refers to men and B to women. We represent a linear relationship between variable W and its determinants separately for groups A and B as follows:

$$logW_i = \alpha_{A0} + \sum_{k=1}^{K} X_{ik}\,\alpha_{Ak} + \varepsilon_{iA}, \forall\, i \in A$$

$$logW_i = \alpha_{B0} + \sum_{k=1}^{K} X_{ik}\,\alpha_{Bk} + \varepsilon_{iB}, \forall\, i \in B$$

Once we estimate the parameters of each model, we can then determine the average salary in each group:

$$\overline{logW_A} = \hat{\alpha}_{A0} + \sum_{k=1}^{K} \bar{X}_{Ak}\,\hat{\alpha}_{Ak}$$

$$\overline{logW_B} = \hat{\alpha}_{B0} + \sum_{k=1}^{K} \bar{X}_{Bk}\,\hat{\alpha}_{Bk}$$

The average wage can differ from one group to another for two major reasons. First, the average characteristics are not identical in group A and group B. Second, the returns of these qualities and the constants of the two models are different. We decompose the differences as follows:

$$\overline{logW_B} - \overline{logW_A} = (\hat{\alpha}_{B0} - \hat{\alpha}_{A0}) + \sum_{k=1}^{K} \bar{X}_{Bk}\,\hat{\alpha}_{Bk} - \sum_{k=1}^{K} \bar{X}_{Ak}\,\hat{\alpha}_{Ak}$$

$$\overline{logW_B} - \overline{logW_A} = \underbrace{\sum_{k=1}^{K}(\bar{X}_{Bk} - \bar{X}_{Ak})\hat{\alpha}_{Bk}}_{Explained\ part} + \underbrace{(\hat{\alpha}_{BO} - \hat{\alpha}_{A0}) + \sum_{k=1}^{K} \bar{X}_{Ak}\,(\hat{\alpha}_{Bk} - \hat{\alpha}_{Ak})}_{Unexplained\ part}$$

In a non-discriminatory labor atmosphere, women would have returns, associated with labor characteristics, identical to that of men (or vice versa).

The first term stands for the wage disparity that would persist in the absence of discrimination. The wage gap here is detected to show the major discrepancies in the labor market qualities of both men and women. This difference does not stem from discrimination, but from the observable individual characteristics (human capital, work experience, etc.).

The second term measures discrimination, i.e., the situation in which the employers' discriminatory practices against females generate a gender wage gap.

4.2. Estimation results

In this paper, I relied on the population and employment survey conducted in 2015 by the Tunisian National Institute of Statistics during my data collection phase. This survey is restricted to male and female workers aged above 18. It provides valuable information related to earnings, marital status, activity sectors, and educational levels. The averages of log-monthly wages are 5.61 and 5.88 for females and males, respectively. This means that the average male-female wage gap is equal to (0.27 = 5.88-5.61).

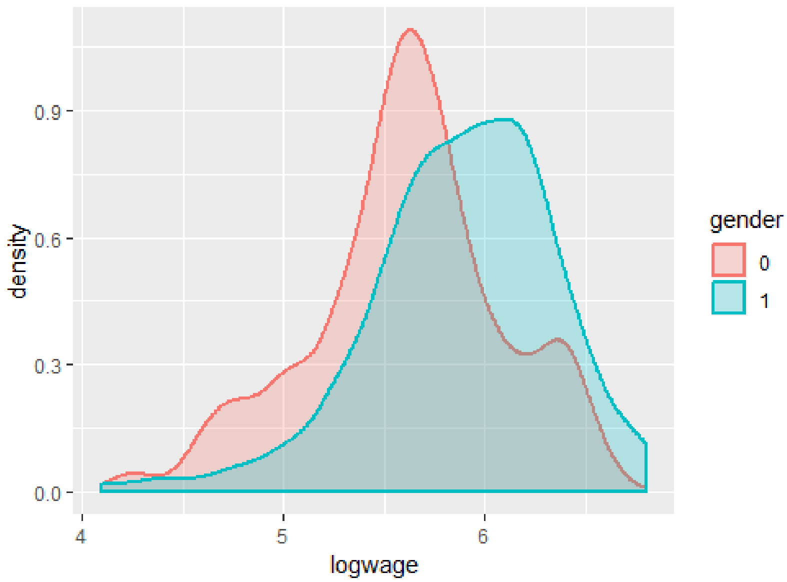

Figure.1–Log wage distribution for both males and females.
Source: Author calculations and the employment survey (INS, 2015).

In figure (1), we represent the distribution of the logarithm of both male and female wages. The male wage density is left-skewed compared to the distribution of women's salaries, implying that females are suffering from wage inequity. We note a distinctive pike in female log wage distribution, which means that most females receive overall lower wages, compared to males. As shown in the bottom of the female curve, we can easily deduce that few females received the same wages as men. However, this observation approves the fact that women suffer from gender wage discrimination.

If we refer to the Oaxaca-Blinder decomposition explained above, group B will correspond to men, while group A will refer to women in our decomposition task. The variable of interest is the logarithm of the net monthly wage.

First, we investigate the composition effect and the unexplained gap. To do this, we need to estimate the wage equation for the two samples separately. Then, we calculate the averages of each variable for the two groups, as shown in the tables below.

	Coefficients of X_A's	Coefficients of X_B's
Intercept	5.509	6.042
Age	-0.002	0.001
Center East	0.000	-0.041
Center west	-0.067	0.077
South East	-0.265	0.074

South-west	-0.003	0.135
Married	-0.259	-0.113
Widowed	0.039	0.006
Divorced	-0.534	0.160
Secondary	0.295	0.229
Tertiary	0.049	0.540
Agriculture	0.399	0.084
Construction, ceramics and glass	-0.191	0.061
Mechanical and electrical	-0.130	0.172
Chemistry	-0.405	-0.199
Textile	-0.688	0.297
Other manufacturing	-0.643	0.087
Oil and gas	-0.232	-0.138
Electricity	-0.060	-0.024
Civil engineering	-0.466	0.156
Commerce	-0.577	0.169
Transport	-0.524	0.200
Hotels and restaurants	-0.264	0.097
Banking and insurance	-0.617	0.354
Repairs	-0.416	0.045
Social and cultural services	-0.557	0.222
Education, health and public administration	-0.482	0.116

Table.3–Estimates of parameters for each group.

	$\overline{X_A}$	$\overline{X_B}$
Intercept	1.000	1.000
North-west	0.009	0.000
Center East	0.055	0.032
Center west	0.018	0.016
South East	0.052	0.061
South-west	0.003	0.013
Age	39.234	38.884
Married	0.649	0.620
Widowed	0.022	0.011
Divorced	0.018	0.016
Secondary	0.714	0.734
Tertiary	0.228	0.195
Agriculture	0.025	0.032
Construction, ceramics and glass	0.009	0.008
Mechanical and electrical	0.052	0.040
Chemistry	0.012	0.016
Textile	0.046	0.045
Other manufacturing	0.028	0.008

Oil and gas	0.000	0.005
Electricity	0.006	0.016
Civil engineering	0.095	0.077
Commerce	0.126	0.113
Transport	0.092	0.098
Hotels and restaurants	0.037	0.034
Banking and insurance	0.025	0.024
Repairs	0.062	0.082
Social and cultural services	0.046	0.055
Education, health and public administration	0.326	0.330

Table.4– Averages of each variable for both male and female samples.

To determine the composition effect, we multiply the estimated coefficients for men by the differences in the average characteristics between men and women for all variables. This presents 0.013 of the overall gender wage gap, which equals 0.27. The composition effect thus represents 4.8% of the entire wage gap between males and females. 4.8% of the wage gap is traced back to average differences between the sexes. In this case, the unexplained gap corresponds to 0.257.

Once we have estimated the decomposition parameters, the results of the aggregate decomposition can be displayed as:

Group	Coefficient (explained gap)	Standard error (explained gap)	Coefficient (unexplained gap)	Standard error (unexplained gap)
0	0.013	0.015**	0.257	0.036**
1	0.005	0.018**	0.265	0.035**

Table.5– Oaxaca-blinder decomposition results

Notes. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

The group column shows the reference from which decomposition was determined. For the model corresponding to group (1), we perceive that the explained gap is 0.005. It is the difference between the average salary of women and the salary that they would receive when no dissimilarity occurs between the qualities of males and females. The unexplained gap corresponds to the difference between the average wage of men and the average salary that females would receive if their characteristics are identical to those of males. Distinguishing between the explained and the unexplained wage gaps varies depending on the chosen reference. For example, as a counterfactual[2], we consider the wages that men would receive if their characteristics correspond to those of women (group=0). Then, we find a composition effect of 0.013 and an unexplained difference of 0.257.

[2] A counterfactual is a fictitious representation of an individual's state in a non-observable situation.

We can then display the detailed results, i.e., the contribution of each variable to the explained and unexplained differences, as shown in the graphs below.

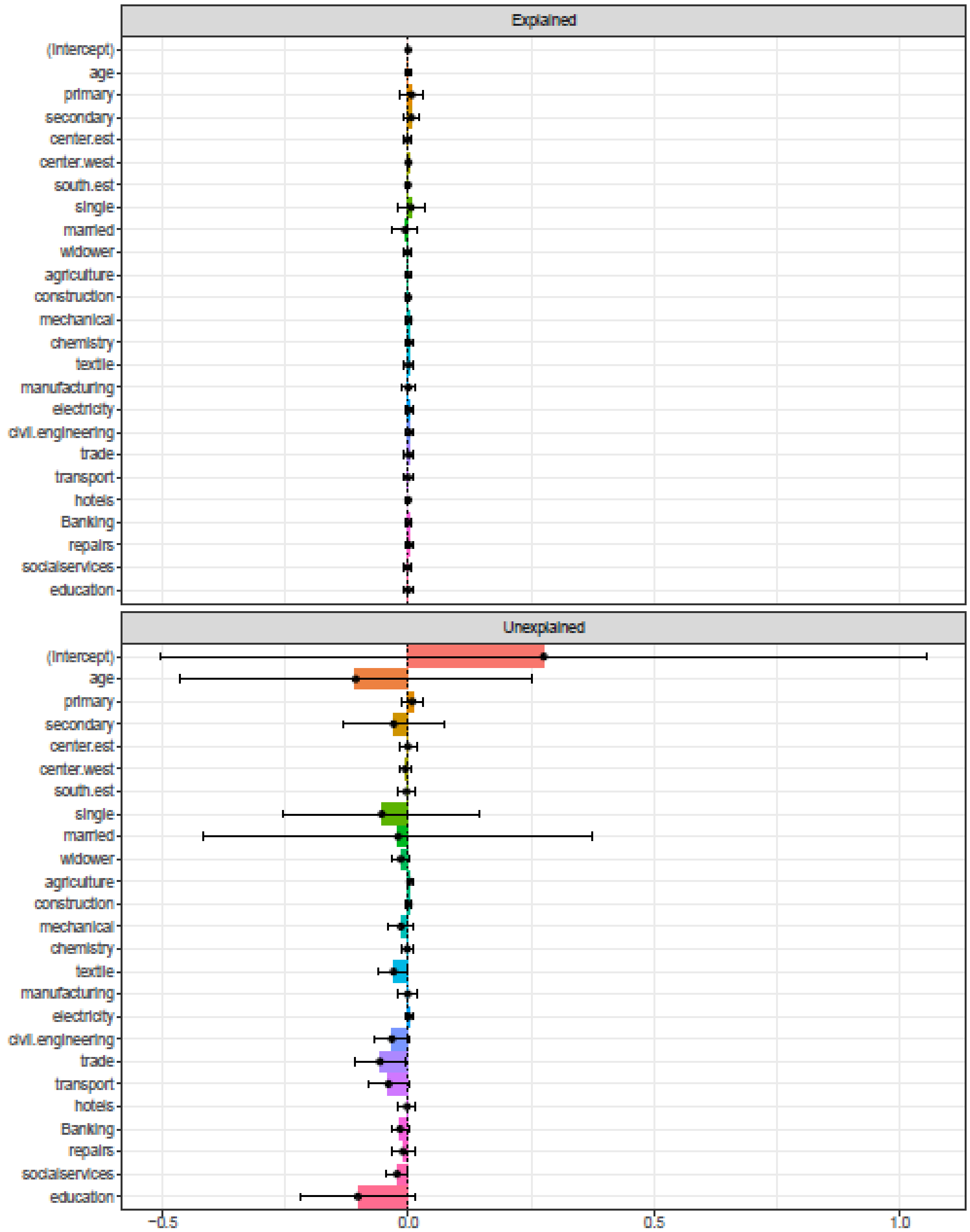

Figure.2–Graphical representation of the explained and unexplained wage gap between males and females.

The upper part of the graph reveals the contribution of each variable to the explained gap. The variable that contributed positively to the explained gap is the primary indicator with a contribution of 0.00689 or about 53% of the overall explained gap. Almost the entire difference in average wages between men and women refers to the fact that women have often reached the primary education level. Note that some additional variables can reduce the unexplained gap. This is the case, for instance, for some educational levels. If women have more appropriate labor characteristics than men, controlling these characteristics will reduce the proportion of differences that can be imputed to the X's.

The lower part of the graph illustrates the unexplained gap by variable. As it is possible to detail the contributions of each variable to the composition effect, we are also able to set for the unexplained gap.

As one of the most important methods, the Oaxaca-Blinder decomposition technique plays a key role, notably in decomposing and evaluating gender wage discrepancies. The remarkable limitation of this approach is its inability to measure the wage gap across the wage distribution. This can be explained by the fact that this method could estimate only the average pay differentials.

In the next section, we will scrutinize how to overcome this problem with counterfactual analysis. The latter helps us measure and decompose the male-female pay gap at every quantile of the wage distribution. The counterfactual analysis permits us to determine whether we are in the presence of a "glass ceiling"[3] or a "sticky floor"[4] situation.

5. Counterfactual analysis

5.1. Counterfactual decomposition technique

An employee's income reflects his or her characteristics, such as education or work experience. Men and women with the same characteristics may receive different salaries. To measure the wage disparity between males and females, we implement a counterfactual distribution. This is suitable for estimating what women would earn if they possess the characteristics of men.

The study of wage differences allows us to figure out the essence of a counterfactual analysis based on distributions. This analysis determines what the result would be if we combine the male conditional wage distribution with the distribution of women's characteristics.

The hypothesis that male and female labor characteristics are indistinguishable, leads us to direct our attention to analyzing the effect of this assumption on women's wages. Otherwise, we crave an answer to the following question: does wage discrimination exist if women had the same characteristics as men?

[3] « Glass ceiling » is an expression meaning that the gender wage gap is bigger at the top of the wage distribution.
[4] « Sticky floor » is a description used to outline the situation where the gender pay gap is more relevant at the bottom of the distribution.

The fictitious representation of an individual's situation (the counterfactual) is difficult to be specified (Heckman, Smith, 1996). Studying counterfactual distributions is one way to properly define this representation. Counterfactual distributions assess the effect of a change in the marginal distribution of covariates on the variable of interest. Besides, we can evaluate a change in the conditional distribution of the outcome variable by taking into account the covariates and counterfactual distributions.

The counterfactual analysis maintains the characteristics of a particular sample and redistributes them on the salary structure of another sample. The key idea is to divide the population into two distinct samples. The first sample represents the reference group, which comprises observations that will be served in the counterfactual wage distribution. The second sample, also known as the counterfactual group, is generated by combining its outcomes with the characteristics of the reference group.

Note that the choice of counterfactual is crucial, particularly for proper interpretation of the decomposition results.

Observable covariates exist in the two samples, while the outcome vector is observable only in the reference population. This means that the counterfactual population is hypothetically formed. There are two scenarios to create a credible counterfactual population:

- The first scenario consists in combining the male wage with the female observable characteristics. In this case, we are about to determine male wages if their characteristics conform to those of women.
- The second scenario is also a conditional wage distribution on observable characteristics. This time, we are interested in determining the wages that women would receive if their characteristics were ascribed to men.

The choice of reference and counterfactual samples depends on one of the two situations described above.

In the first scenario, the reference group is composed of women since men will receive female labor market characteristics instead of their observable characteristics. This means that the male group represents the counterfactual sample. It is a hypothetical situation where we distribute the vector of male wage to female characteristics as if they belong to men. On the contrary, the second scenario provides an opposite explanation. Our analysis is based on the first situation.

To study the differences in pay between men and women, we coded our variables. The male population was coded as 1 while the female population was coded as 0. The variable y_j

represents wages and x_j indicates the labor market characteristics that affect wages for both populations.

The conditional distribution functions $F_{y0|x0}(y|x)$ and $F_{y1|x1}(y|x)$ describe the stochastic assignment of wages to workers, according to the individual characteristics of women and men, respectively. We consider $F_{y\langle 0|0\rangle}$ and $F_{y\langle 1|1\rangle}$ the functions of the observed wage distribution for the female and male population, respectively. $F_{y\langle 0|1\rangle}$ represents the income distribution function that would have prevailed for women if they had been confronted with the male wage scale.

$$F_{y\langle 1|0\rangle}(y) = \int_{\chi_1} F_{y1|x1}(y|x) dF_{X_0}(x)$$

This distribution is called counterfactual because it is not observable. In fact, this distribution is the result of incorporating the conditional distribution of male wages into the distribution of female characteristics.

Let $F^{\leftarrow}$ be the quantile function. According to (Oaxaca, 1973) and (Blinder, 1973), the gender wage difference based on the conditional quantile regression can be decomposed as follows:

$$F^{\leftarrow}{}_{Y\,\langle 1|1\rangle} - F^{\leftarrow}{}_{Y\,\langle 0|0\rangle} = \left[F^{\leftarrow}{}_{Y\,\langle 1|1\rangle} - F^{\leftarrow}{}_{Y\,\langle 1|0\rangle}\right] + \left[F^{\leftarrow}{}_{Y\,\langle 1|0\rangle} - F^{\leftarrow}{}_{Y\,\langle 0|0\rangle}\right]$$

Quantile regressions attempt to evaluate how conditional quantiles $F^{\leftarrow}$ (y|x), defined by $F^{\leftarrow}{}_{Y\,\langle y|x\rangle}(\tau) = \inf\{y \in Y_j : F_{y\langle y|x\rangle}(y) \geq \tau\}$ change when the determinants $X \in R^p$ of the variable of interest vary.

These quantile functions determine the wage gap between males and females based on the counterfactual distribution. This method decomposes the wage difference formula into two terms. The first term represents the effect of differences on characteristics whereas, the second term focuses on the differences in the wage structure.

5.2. Counterfactual gender wage gap decomposition results

We extracted our gathered data from the 2015 employment and population survey of male and female workers in order to estimate wage decompositions.

The dependent variable is the log of wage. The covariates are age, marital status, educational attainment (with three levels: primary, secondary, and tertiary), activity sector, and gender indicator which defines both reference and counterfactual samples.

We estimate conditional distributions using quantile regression techniques. The first step consists in defining the reference and counterfactual populations. In the second step, we measure the wage decomposition according to the counterfactual distribution. As a result, we derive composition, structure, and total effects.

We can display the detailed outcomes in either graphs or tables, as it is shown below.

	Quantile Effects		
Quantile	Structure	Composition	Total
0.1	0.29 (0.010)	0 (0.015)	0.29 (0.016)
0.2	0.22 (0.012)	0 (0.000)	0.22 (0.013)
0.3	0.22 (0.000)	0 (0.004)	0.22 (0.005)
0.4	0.34 (0.013)	0 (0.009)	0.34 (0.004)
0.5	0.31 (0.002)	0 (0.003)	0.31 (0.003)
0.6	0.29 (0.006)	0 (0.007)	0.29 (0.006)
0.7	0.34 (0.006)	-0.029 (0.005)	0.32 (0.005)
0.8	0.22 (0.003)	0 (0.002)	0.22 (0.002)
0.9	0.18 (0.004)	-0.095 (0.005)	0.087 (0.003)

Table. 6–Quantile effects of gender wage gap
Source: Author calculations.

Notes. Standard errors are in brackets. Reference group is female. Counterfactual group is male.

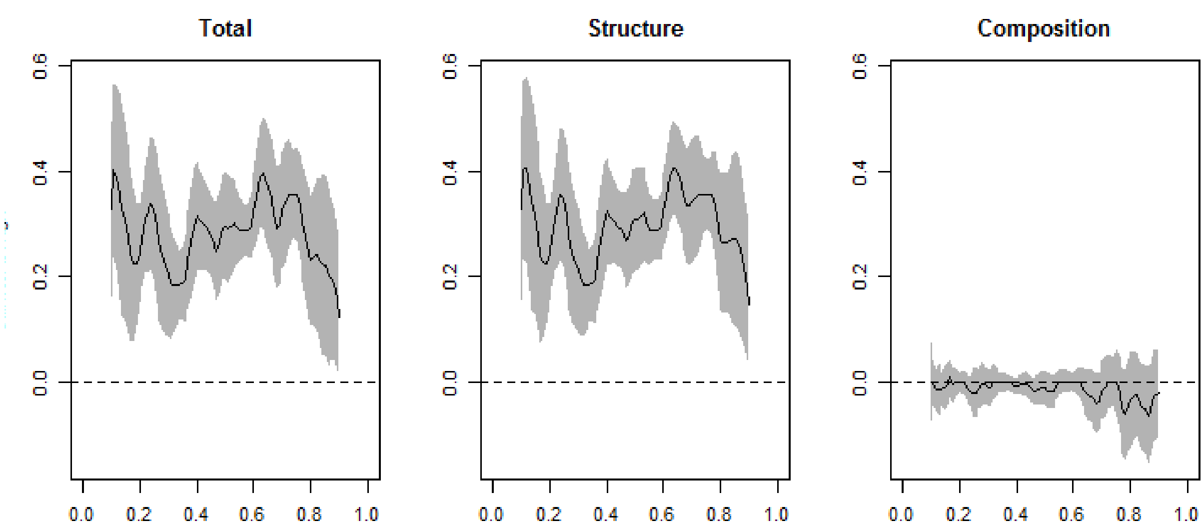

Figure.3–Wage decomposition with respect to gender: quantile regression estimates
Source: Author calculations.

The composition effect corresponds to the male-female wage gap based on male characteristics that are similar to those of women.

The composition effect of wage difference is related to observable characteristics, while the structure effect refers to differences in coefficients. The total effect refers to the gap between the observable male wage distribution and the counterfactual distribution. The results show that men earn higher wages than women, even if both genders have the same labor market characteristics.

We notice that the graphic representation of the composition quantile effect overlaps on the horizontal axis, implying that the composition effect is approximately equal to zero. The composition effect is negligible in explaining the gender wage gap.

The estimates of the quantile effect represented in the table confirm our deductions. All the quantile effects are equal to zero except at the seventh and ninth quantiles, where the measured values differ slightly from zero (-0.029 and -0.095, respectively).

Concerning the structure effect, the male-female wage gap decreases at the first quantile. It stagnates at the second and the third quantiles. Then, it increases again at the fourth quantile. At the next two quantiles, the wage gap drops. But it rises again at the seventh quantile. From then on, the wage differentials decrease. These fluctuations show that gender wage gap is not constant across quantiles. The wage gap between men and women varies from 18% to 34% across quantiles.

6. Conclusion

In Tunisia, the percentages of female workforce (28.9%) and female unemployment (22.9%) are shameful. The worst thing is that female workers, despite their limited number, are working in lower paid occupations compared to men.

According to this female situation in the labor market, it is crucial to measure and decompose the male-female wage differentials. We divide the gender wage gap into two parts: one emanates from endowments, while the other refers to gender discrimination. For this purpose, we introduced the latest R package for estimating quantile effects and wage decompositions. The counterfactual package implements the estimation of both the composition and structure effects of the gender wage gap. We graphically illustrate the persistence of the gender pay gap in the Tunisian labor market.

Our counterfactual decomposition method provides stochastic simulations of wage distributions by combining the bootstrap technique with the quantile regression. Our empirical findings show that the gender wage gap in the Tunisian labor market varies between 18% and 34%. The counterfactual analysis reveals that the combination of women’s returns with male observable characteristics is used to create a counterfactual distribution. The latter allows, first, to calculate the wage gap at each quantile and decompose it across the wage distribution.

The summarized results show that the total effect and the structure effect are perfectly identical. That is to say the gender wage gap derives mainly from the discriminatory practices against women. Differences in terms of male-female characteristics do not account for gender pay differentials. The composition effect is approximately equal to zero in the whole wage distribution. Overall, the composition effect plays a negligible role in explaining the gender wage gap.

7. References

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