INDUSTRY FLEXIBILITY AND GENDER PAY GAP: EMPIRICAL EVIDENCE FROM ITALY

Annemarija Apine

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Abstract

Despite a decrease in the gender pay gap over the last century, the narrowing has plateaued in the eurozone. Individual characteristics, for example, education no longer explain these differences in remuneration. Accordingly, alternative theories have been proposed, such as the impact of industry flexibility and non-linear returns of labour. This paper aims to find out whether the hypothesis of industry (in)flexibility as a driver of the pay gap applies to the Italian labour force. For that different types of regression models are applied to estimate income using social security contribution data (LoSaI data set) and the Italian Labour Force Survey. Additionally, a separate regression is modelled for the industry gender pay gap and the overall pay gap is considered using the Blinder-Oaxaca decomposition. The results suggest that the main driver behind the gender pay gap in this sample is convexity in the relationship between hours worked and income, i.e., disproportionately rewarded overtime, in a situation where women generally work fewer hours. However, alternative industry flexibility characteristics, such as working Saturdays or the ability to work from home do not seem to significantly impact the gender pay gap.

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1 Introduction

Despite a convergence in wages between men and women in the last century, there still exists gender pay gap and a part of it is not necessarily explained by individual characteristics. One of the proposed theories to explain it is industry flexibility, in particular non-linearity in returns on hours worked – if working overtime is disproportionately rewarded and women tend to work lower hours then it can contribute to the gender pay gap. At the moment industry flexibility as an explanation has not been explored in detail in regards to the gender pay gap in Italy and generally there are relatively few papers focusing on this idea outside the US. This paper examines the relationship between industry flexibility characteristics and the gender pay gap for the Italian workforce using panel data from the LoSaI data set on social security contributions and data from the Labour Force Survey. It looks at a variety of characteristics describing industry flexibility in income regressions, as well as estimates the industry pay gap. Furthermore, the gender pay gap is decomposed using the Blinder-Oaxaca decomposition into explained and unexplained components. The results suggest that income and hours worked relationship is indeed non-linear and this convexity is the main identified explanatory component for the gender pay gap suggesting necessary improvements in the way work is organised if gender pay gap is to be decreased.

2 Theoretical background

2.1 Gender pay gap: different explanations

The gender pay gap is a well-studied subject, providing different explanations over the years. It is a continuously evolving field, too, since many advances have been made toward gender equality: in her American Economic Association presidential address Goldin (2014) describes a narrowing "between men and women in labor force participation, paid hours of work, hours of work at home, life-time labor force experience, occupations, college majors, and education" (p. 1091). Indeed, using microdata Blau and Kahn (2017) provide evidence that between 1980 and 2010 the gender pay gap decreased considerably and by the end of 2010, it was industries and occupations, rather than conventional human capital characteristics, that were the main explanatory variables for the remaining pay gap. The hypothesis that education and cognitive skills in the past few decades explain little of the pay gap, is also supported by O'Neill and O'Neill (2005) using data from the year 2000.

However, the narrowing of the pay gap has not been a uniform process across different groups. According to Kassenboehmer and Sinning (2014), in the 1993-1995 and 2004-2008 periods the narrowing of the pay gap was much more pronounced in the lower income deciles and in the latter period there was a greater unexplained gap at the ninetieth than at the fiftieth percentile. This also appears to be true for our country of focus – Italy – where the gender pay gap is higher for more educated women (Castagnetti et al., 2018). Furthermore, complexities arise when looking at the pay gap at the intersection of multiple marginalised identities (Paul et al., 2018). To exemplify, in Britain the pay gap and its dynamics over time differ by race (Breach & Li, 2017).

Apart from the already mentioned drivers of the pay gap, there exist alternative hypothesis. One of them is discrimination, such as the unexplained differences in the Oaxaca–Blinder decomposition, which according to Blau and Kahn (2017) while relatively standard in literature and discussed in their own paper, are hard to take for conclusive evidence of discrimination due to possible unmeasurable characteristics or influence of discrimination on explanatory variables; while studies with smaller and more detailed samples (such as MBA graduates) may solve some of these issues, additional selection can impact the results too. While there exist studies showing hiring bias (Neumark et al., 1996; Reuben et al., 2014) and parental status discrimination toward female applicants (Correll et al., 2007), they do not necessarily explain the dynamics of gender pay gap over lifetime. Other papers mention soft skills and psychological differences as possible explanation for the gender pay gap: women's lack of bargaining skills (Babcock et al., 2003), gender norms (Bertrand et al., 2013), and lower likelihood to compete (Niederle & Vesterlund, 2007), the last disputed by Manning and Saidi (2010) who argue that the effect of performance pay on earnings is modest and does not differ markedly by gender.

Furthermore, Blau and Kahn (2017) conclude that psychological attributes explain a relatively small part of the gender pay gap compared to occupation and industry effects, and Goldin (2014) argues that while the alternative explanations have some merit, they do not explain the pay structure with respect to hours that pays a role in the gender pay gap.

2.2 Wages and working hours: the impact on gender pay gap

Goldin (2014) proposes that the main cause of the gender pay gap is the value placed on the hours worked, that is the (non-)linearity of earnings: non-linearity is correlated with a higher wage gap compared to constant returns on hours worked. She singles out two important aspects – flexibility and continuity – with the idea that in certain occupations an employee who is around less becomes less valuable (either because it is costly to communicate the information to a replacement employee or because they miss out on meetings), thus, employers impose penalties for employees who want to work fewer hours or prefer more flexible employment – the opposite of compensating differentials.

There is plenty of evidence detailing the differences in temporal choices between genders: generally women work lower hours, have lower employment rates and are more likely to be employed in part-time work. This is particularly true for Italy: in 2009 only 46 % of Italian women of working age had a job, significantly below the EU average and the percentage of women working a part-time job was around 5 times higher than that of men. (Boca & Giraldo, 2013)

However, aforemetioned statistics alone would not be sufficient to explain the gender pay gap since they do not consider the potential non-linearity of returns. Although several models have been designed to show that wage-work-hour relationship is non-linear, the exact shape of the function is debated. Barzel (1973) suggested that the average hourly wage, in general, does not equal the wage for the marginal hour, and that the productivity of labour, and therefore wage, follows an S-shaped curve. Moffitt (1984) proposed a quadratic model of the hour-wage relationship. It should be noted that linearity is not the only possible invalid assumption in the standard labour supply model: several studies have also shown that the choice of hours can be restricted (Dickens & Lundberg, 1993). Building upon Moffitt's model and the assumption of restricted hours, Tummers and Woittiez (1991) empirically showed the non-linear budget constraint in the Dutch labour market in which it appears that wages decrease with hours worked. Wolf (2002) not only shows non-linearity in the inverse U-shape using spline functions, but emphasises that the function differs by sector. Biddle and Zarkin (1989) using instrumental variables in a simplified model also show that the relationship is dome shaped using a sample of American men. In one of the most recent papers, Using the 2015 American Working Conditions Survey which records actual and reservation (i.e., desired) working hours, Männasoo (2022) confirms the non-linearity for both genders: a hump shaped relationship between hours and hourly wages which explains in part the remaining gender pay gap.

In particular, one of the main mechanisms contributing to the gender pay gap is the compensating wage differential theory: if women prefer shorter hours while longer hours are disproportionately rewarded in certain occupations, those occupations would have a higher gender pay gap (Goldin, 2014). This idea is supported by Gicheva (2013) who empirically shows that there is a non-linear positive relationship between weekly hours and hourly wage growth, particularly that for those working more than 47 hours per week, 5 extra hours were associated with a 1% increase in annual wage growth. Cha and Weeden (2014) showed that the increase in returns to working over 50 hours per week (”overwork”) has slowed the convergence of the gender pay gap from 1979 to 2009 (see their paper for explanations on rising prevalence of overwork). Although limited to men in the period of 1979–2006, Kuhn and Lozano (2008) also reported rising wage returns to overwork. Cha and Weeden (2014) also note that women are less likely to enter and stay in jobs that require extremely long hours (Cha, 2013), generally explained as caused by traditional views of family dynamics (Cotter et al., 2011; Hochschild & Machung, 2003). Similarly Männasoo (2022) explains that inflexible jobs or jobs with low levels of autonomy have a higher gender pay gap; however, for on-site jobs (as opposed to remote working) the desired and actual working hours at the intensive margin render the pay gap statistically insignificant. This could be related to the findings of Chung and van der Horst (2020) that certain types of flexible working arrangements can potentially exacerbate gender inequalities by allowing men to devote more time to their jobs while it is not always plausible for women.

Lastly, not all occupations and industries are made equal when it comes to compensating wage differentials and overwork. The gender pay gap is particularly pronounced in professional and managerial occupations where other aspects such as educational attainment and continuous work experience should bridge the gap; Cha and Weeden (2014) propose that the ”greedy” nature of these occupations (Jacobs & Gerson, 2021), accompanied with characteristics of the women in these occupations – with middle-class norms of “intensive mothering” (Lareau, 2011) and the high likelihood of having overworking spouses (Cha, 2010) – explain the lack of convergence in the pay gap. Goldin (2014) herself demonstrates that certain characteristics of occupations that are associated with higher time demands and lower worker substitutability (time pressure, contact with others, establishing and maintaining interpersonal relationships, structured vs. unstructured work, and freedom to make decisions), are associated with a higher gender pay gap. She exemplifies this idea with case studies of occupations. Pharmacists with linear returns with respect to hours and negligible penalty for breaks in the career have an occupation with one of the lowest gender pay gaps, while in law where income becomes increasingly convex with respect to wages as the career progresses, so does the pay gap. Two additional findings to note from her work: within-occupation differences in earnings are far more important than gender distribution between fields, and that in tech, it is the occupations, rather than industries that are more associated with gender equality in earnings.

3 Data and Methodology

3.1 Data sources: the sample and variables

To examine the gender pay gap with a wider set of variables, two data sources were used: the Italian National Institute of Statistics (Istat) Cross-sectional Quarterly Labour Force Survey, and Longitudinal Sample INPS (LoSaI) which records the social security contributions of workers in Italy. Both data sets to some extent can be integrated on an industry level due to compatible codification of economic activities (ATECO) in roughly 90 industries; this is why the time frame has been chosen between 2011 and 2016 when the same classification system is used.

The Quarterly Labour Force Survey aims to obtain information on the work situation, employment search, and attitudes toward the labour market from the working-age population. It focuses on household members residing in Italy. The sampling design adopted in each quarter is a two-stage design with stratification of the first-stage units (municipalities) and second stage units (households). To reduce fluctuations, the survey data each household is interviewed in four quarters. In each quarter, around 1,400 municipalities and 70,000 households are covered. To ensure that the sample is representative, a carry-over coefficient is implemented. (*Aspetti metodologici dell'indagine*, 2014) The variables used in this paper include year, age, type of employment (full-time vs. part-time), level of educational attainment, weekly hours worked, monthly net salary excluding other monthly payments (hereinafter "monthly salary"), aforementioned ATECO industry classification, and several questions used to quantify industry flexibility such as whether the person worked overtime, evenings, Saturdays, as well as did they work from home in the week preceding the survey.

The LoSaI dataset observations come from taxpayers in Italy, sampling by the date of birth (dates 1 and 9 of every month), creating a longitudinal panel. Each person is assigned a unique identification code, which is valuable for observing certain fixed effects. The variables used from the LoSaI include gender (male or female), age, year and month, annual income in EUR, employment status (employed vs. unemployed), type of employment (full-time vs. part-time), ATECO industry classification, occupation (apprentice, executive, middle manager, white collar employee, blue collar employee, and other), type of contract (fixed or temporary), size of the company and regions.

Borrowing Goldin's methodology, this paper focuses on full-time full-year (here defined similarly as having worked at least 9 months out of the year) workers between the ages 25 and 69 (of working age and likely to have graduated), although unfortunately in the labour survey sample, full-year workers could not be differentiated. In the LoSaI sample, only one observation per person per year was left to avoid skewed weights since income is measured annually. In both samples only the industries with at least 25 observations of each gender were kept to ensure extreme cases do not impact the regressions. After narrowing down the two samples based on these characteristics, unreported wages and other empty observations were ommitted under the assumption that they are random. It should be mentioned that additional questions from the Istat survey such as whether the employee had a choice in how many hours they worked and a choice of where to work, albeit relevant to industry flexibility, were not included in the variable list: there was a perfect correlation between the people who responded to this question and did not report their monthly salary, unfortunately calling into question the assumption of randomness in empty observations.

3.2 Methodology

3.2.1 Regressions on the LoSal data set

Mainly two regression models were used to analyse the LoSaI panel data: random effects and Mundlak's correlated random effects model (Mundlak, 1978). The random effects model was mainly used for testing the model specification as it does not account for the likely individual-specific effects present in the wage estimation (such as preferences). While the random effects model might not be consistent and should not be used for estimation, it still makes for an interesting comparison between the two models.

First, the classic random effects model, albeit not taking into account unobserved heterogeneity, is still useful to consider. It estimates the yearly log income y for each individual i at time t using the following formula:

$$y_i = X_{it}\boldsymbol{\beta_i} + \eta_i + \varepsilon_{it}$$

$$v_{it} = \eta_i + \varepsilon_{it}$$

where the variables are age and dummies for gender, year, occupation, firm size, and region, as well as the ATECO code in the second regression. The composite error v_{it} consists of η_i – the unobserved individual effect – and ε_{it} – the idiosyncratic error term. In addition, intragroup (for each individual) correlation has been allowed for standard errors.

Secondly, Mundlak's correlated random effects model was constructed. Furthermore, it was used to test whether a random or fixed effects model would be more appropriate for estimating income. It is constructed similarly estimating the yearly log income y for each individual i at time t:

$$y_i = X_{it}\boldsymbol{\beta_i} + \bar{X}_i\alpha + \eta_i + \varepsilon_{it}$$

The model has the same controls and error terms but in this case the group-means of time-variant variables are included. It relaxes the assumption that the observed variables are uncorrelated with the unobserved ones. Moreover, within this model the Mundlak test was performed where the null hypothesis that the group-means equal to 0 was rejected, thus, suggesting that the fixed effects model (rather than random effects) is more appropriate for estimating income. However, since the variable of interest, gender, is time-invariant in the sample, and therefore the fixed effects model is not applicable, the Mundlak model will be used instead.

3.2.2 Regressions on the Labour Force Survey data set

Since the monthly salary variable is censored in the data set (values below EUR 250 are recorded as EUR 250 and similarly for those above EUR 3000), an interval regression model (with robust standard errors) was chosen to account for such cases. Additionally, a multivariable fractional polynomial model was used in combination with the interval regression model to consider the possibility that income is not a linear or quadratic function of hours worked.

The interval regression equation (a generalisation of Tobin's tobit) estimates continuous monthly log salary y_j for independent variables X_j (weekly hours and squared weekly hours worked, dummies for gender, education, year, region, type of contract, age, working overtime, evenings, Saturdays, from home) with a normally distributed error term for individual j:

$$y_j = X_j\beta + \varepsilon_j$$

$$\varepsilon \sim N(0/\sigma^2)$$

To do so it maximises the log likelihood:

$$lnL = -\tfrac{1}{2}\sum_{j\in C}\{(\frac{y_j - x_j\beta}{\sigma})^2 + log2\pi\sigma^2\} + \sum_{j\in L} log\Phi\{(\frac{y_{Lj} - x_j\beta}{\sigma})\}$$
$$+\sum_{j\in R} log\{1 - \Phi(\frac{y_{Rj} - x_j\beta}{\sigma})\}$$

where for observations $j \in C$ we observe y_j, observations $j \in L$ are left-censored (i.e., $y_j \leq y_{Lj}$ where $y_{Lj} = log(250)$) and observations $j \in R$ are right-censored (i.e., $y_j \geq y_{Rj}$ where $y_{Rj} = log(3000)$). $\Phi()$ is the cumulative standard normal distribution. (StataCorp, 2021)

Finally, Stata's multivariable fractional polynomial (MFP) model command was used to select the MFP model that best predicts the outcome variable y_j given the independent variables. It deviates from the standard linear model and transforms variables if necessary by assigning powers to them. It should be noted that is still takes into account that salary is censored in the data set (StataCorp, 2021). This procedure may not only more accurately estimate the salary, it can also be used to identify which functional form of the variable is more appropriate (Binder et al., 2013).

3.2.3 Pay gap regression

To estimate the effect of different industry characteristics, the industry-specific pay gap was estimated using an OLS regression model and Labour Force Survey data. It estimates the pay gap y_i, expressed as the ratio between female and male wages in each industry i, using industry means for different characteristics relevant to flexibility (e.g., percentage of people who worked overtime) as independent variables:

$$y_i = X_i\beta + \varepsilon_j$$

Additionally, for each industry there were two variables describing estimated convexity in returns on hours worked: the ratio of hourly wages when working 40 versus 50 hours and the ratio when working 40 versus 60 hours per week. These hourly wages were estimated for each industry separately by using an interval model similar to the one described previously and using weekly hours and weekly hours squared as independent variables. Accordingly this ratio measures the disproportionate rewards of working overtime in each industry, assuming the quadratic model for the hour-wage function. To exemplify, an industry where the hourly wage is higher for those working 50 hours than for those working 40 hours disproportionately rewards overtime.

3.2.4 Blinder-Oaxaca decomposition

Lastly, to consider which of the variables used in the regression models potentially could explain the gender pay gap, a Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973) was performed using data from the Labour Force Survey. In this two-fold version of the decomposition, the difference of mean log salaries (R) between the two groups (male and female) is separated into two components Q and U:

$$R = Q + U$$

where

$$Q = [E(X_M) - E(X_F)]'\beta^*$$

and

$$U = E(X_M)'(\beta_M - \beta^*) + E(X_F)'(\beta^* - \beta_F)$$

Q is the "explained" part arising from differences between male and female coefficients, meanwhile U is the "unexplained" component usually attributed to discrimination. It's important to note that it may also arise from differences in unobserved variables. X_M and X_F are explanatory variables in separate linear log salary regressions with their respective coefficients β_M and β_F. β^* is some nondiscriminatory coefficients vector, in this case calculated via a pooled regression (Neumark, 1988) that includes group indicators to avoid distortion of the results due to the residual group difference spilling over into the slope parameters (Jann, 2008).

3.3 Results

3.3.1 Main characteristics by gender

Table 1 lists some of the main statistics describing female labour market participation in comparison to their male counterparts. In both data sets women earn comparatively less – between 10 to 20 % on average. However, it appears that women as a group earn a marginally higher mean hourly wage. A smaller proportion of women are employed in managerial roles which are typically associated with higher wages. Furthermore, women lean toward white collar jobs while the opposite is true for blue collar jobs that men gravitate toward.

Additionally, according to the Labour Force Survey women on average work only 36.5 hours compared to men's 39.6 hours. They are also less likely to work more than 40 hours per week (the maximum working hours not including overtime) and report having worked overtime in the past week. Interestingly the proportion of individuals reporting working overtime is considerably lower than those reporting having worked more than 40 hours.

Table 1: Income estimation using the LoSaI data set – random effects and Mundlak models

	Male	Female
LoSaI		
Mean yearly income	30095	24978
Proportion working for a small firm	23.0%	22.7%
Executive	1.6%	0.8%
Middle manager	4.9%	4.0%
White collar employee	29.2%	63.0%
Blue collar employee	62.3%	29.7%
Apprentice	1.6%	2.3%
Other	0.3%	0.3%
Labour force survey		
Mean monthly salary	1474	1320
Mean weekly hours worked	39.6	36.5
Mean hourly income	8.73	8.80
Proportion with higher education	14.6%	27.5%
Proportion working more than 40 hours per week	11.3%	6.1%
Proportion working overtime	5.7%	3.7%

3.3.2 Wage estimations

Despite the differences in methodology, specification and models used, in both data sets, the wage estimation demonstrates impact of industry choice and variables characterising flexibility on wages and that it might explain a part of the gender pay gap.

Using the LoSaI data set (Table 2) we can see that being female has a significant negative impact on income. Absent of controls for the industry, in the random effects model (I) it has a negative impact of 31.5 log points (or around 37%) while in the Mundlak model (II) – negative 27.5 log points (32%). The difference between these two coefficients could be explained by the fact that the Mundlak model also takes into account unobserved individual characteristics such as preferences and accordingly has a stronger explanatory power (higher overall R^2). However, if the model controls for ATECO industries, both of these are significantly lower: being female has a negative effect of 22.7 log points (25%) in the random effects model (III) and a negative effect of

19.6 log points (22%) in the Mundlak one (IV) which again has a higher R^2 compared to the random effects model.

Table 2: Income estimation using the LoSaI data set – random effects and Mundlak models

	(I) RE	(II) Mundlak	(III) RE	(IV) Mundlak
Female	-0.315^{**}	-0.275^{**}	-0.227^{**}	-0.196^{**}
ATECO	No	No	Yes	Yes
Controls[a]	Yes	Yes	Yes	Yes
N	355,663	355,663	355,663	355,663
Within R^2	0.011	0.013	0.017	0.020
Between R^2	0.230	0.305	0.324	0.381
Overall R^2	0.252	0.309	0.306	0.347

[a]Controls for age, year, occupation, firm size, and region.
**Passes the test for significance at the 1% level.

Similar trends can be observed when using the Labour Force Survey data set (Table 3). Adding more specifications related to industry flexibility decreases the significant negative coefficient associated with being female. Absent of these variables (V), the coefficient is -0.177 or around 19%, lower in magnitude than that observed in the LoSaI data set (possibly due to different controls) but still considerable. If we add the variables accounting for weekly hours worked (columns VI, VII, VIII), the negative effect decreases in magnitude by roughly 15 log points. Additionally, it offers different specifications for the effect that worked hours has on the salary: (VI) considers hours, (VII) hours and squared hours, while the MFP model (VIII) replaces the worked hours variable from the linear model with alternative variables $ln(\frac{Z}{10})$ and $(\frac{Z}{10})^{0.5}$ where Z stands for hours worked. The coefficients for these variables are denoted MFP β_1 and β_2 accordingly. Both the squared hours model and the MFP model are convex (hour and log income relationship) for the values present in the data set.

Further we can consider not only hours worked, but specific flexibility characteristics such as working overtime, evenings, Saturdays, and working from home. The addition of these (column IX for the linear model and X for the polynomial model) further reduces the negative impact of being female by several percentage points. All of these coefficients are statistically significant and have a positive impact on income, apart from working Saturdays. It should be noted that the additioin of these coefficients alters the alternative variables proposed by the MPF function for the hours worked: they now are $(\frac{Z}{10})^{-0.5}$ and $\ln(\frac{Z}{10})$ and their respective coefficients are denoted in Table 3 as before.

Lastly, ATECO industry dummies were added (XI) to check whether there are additional effects from industries not captured in the aforementioned flexibility variables. Indeed, controlling for industries, decreases the negative coefficient significantly in magnitude to -0.124. It also suggests that the negative effects of working Saturdays do not hold up within industries. It should be noted that with so many explanatory variables some correlation between them is inevitable but it's still useful to keep the variables to consider the different effects they can have on income.

Table 3: Salary estimation using the Labour Force Survey – interval and multivariable fractional polynomial models

	(V) Interval	(VI) Interval	(VII) Interval	(VIII) MFP	(IX) Interval	(X) MPF	(XI) Interval
Female	-0.177^{**}	-0.162^{**}	-0.163^{**}	-0.162^{**}	-0.158^{**}	-0.157^{**}	-0.124^{**}
ATECO	No	No	No	No	No	No	Yes
Weekly hrs		0.006^{**}	-0.0013^{*}		-0.0011		-0.008^{**}
Weekly hrs^2			0.0001^{**}		0.0001^{**}		0.0002^{**}
MFP β_1				-0.678^{**}		2.813^{**}	
MFP β_2				0.951^{**}		0.952^{**}	
Overtime					0.084^{**}	0.084^{**}	0.060^{**}
Evenings					0.067^{**}	0.068^{**}	0.050^{**}
Saturdays					-0.027^{**}	-0.027^{**}	0.007^{**}
WFH					0.041^{**}	0.037^{**}	0.041^{**}
Controls[a]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	363,350	363,350	363,350	363,350	359,117	359,117	359,117
Log likelih.[b]	-91497.2	-89762.5	-89652.8	-89636.4	-86546.6	-86516.6	-67096.5

[a]Controls education, year, region, type of contract, age.
[b]Log pseudolikelihood.
**Denotes significance at the 1 % level.

For illustrative purposes the relationship between hours worked (x) and the log salary (y) as estimated in the (IX) interval model is depicted in Figure 1. It is plotted using the following formula:

$$y = 7.660 - 0.0011x + 0.0001x^2$$

while for the (X) MFP model (Figure 2) it is plotted using the formula:

$$y = 7.073 + 2.813(\frac{x}{10})^{-0.5} + 0.952ln(\frac{x}{10})$$

Both appear to be convex which was confirmed to be true via derivative calculations for all of the models in columns VII, VIII, IX, X, XI for the range of hours in this data set (18-60 hours). The main difference between the MFP models and interval models is that in the linear models (including the ones not plotted here) salary is increasing in hours worked, however, in the MFP models there is a slight dip around the 22 hour mark.

Figure 1: The relationship between weekly hours worked and log income in the (IX) interval model (Wolfram—Alpha, 2023b)

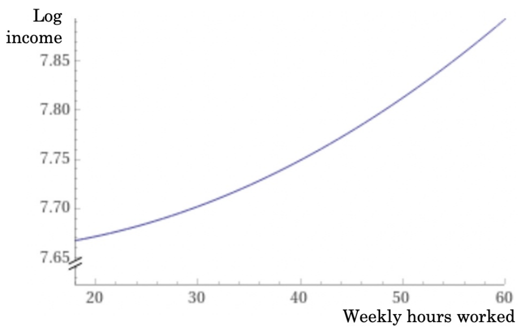
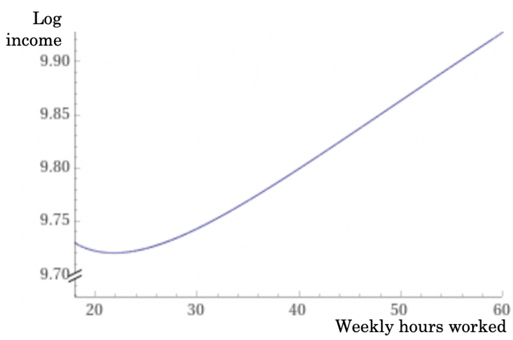


Figure 2: The relationship between weekly hours worked and log income in the (X) MFP model (Wolfram—Alpha, 2023a)



3.3.3 Pay gap estimation

Table 4 summarises the gender pay gap estimation in 83 industries. It appears that industries where the hourly wage ratio for working 40 versus 50 hours is lower, female to male wage ratio is lower (there is a positive correlation of 10.1%). In other words, industries which disproportionately reward overtime, have a higher gender pay gap. However, the same correlation cannot be observed for the 40 to 60 hour wage ratio. In fact, there exists a negative correlation when it comes to working extreme overtime and the gender pay gap. Here it should be noted that when estimating the hourly log wages for each industry it became apparent that the hours worked and wage relationship is not necessarily in line with the one observed in the previous section (Table 3) and differed between industries.

Most other variables do not seem particularly significant when it comes to estimating the gender pay gap with the exception of working evenings which also has a negative impact on the female to male wage ratio. Overall, considering the adjusted R^2, industry flexibility, particularly variables expressing non-linearity in returns to hours worked, has some power in explaining the gender pay gap but it is relatively low.

Table 4: Gender pay gap estimation using the Labour Force Survey – OLS model

	All variables	Select variables
40/50 hr wage ratio	0.101**	0.085**
40/60 hr wage ratio	-0.041**	-0.034**
Evenings	-0.023*	
Weekly hrs	-0.001	
Weekly hrs^2	0.000	
Overtime	0.023	
Saturdays	0.011	
WFH	0.039	
N	83	83
Adjusted R^2	0.117	0.128

**Denotes significance at the 1 % level.
*Denotes significance at the 5 % level.

3.3.4 Blinder-Oaxaca decomposition

Table 5 decomposes the difference between male and female log salaries which is 0.133 into the explained and unexplained components via Blinder-Oaxaca decomposition. The explained component is negative, indicating that these variables cannot explain the difference well while the unexplained component is more than 100% of the gap, indicating some combination of discrimination and effect from unobserved variables.

Looking at some select variables we can notice that, for example, education does not explain the gender pay gap (its contribution is -0.044): the effect of education on income is positive and the proportion of women with higher education is almost twice that of men in this data set. In fact, the variable with the greatest explanatory power is squared weekly hours (contribution of 0.040). Meanwhile weekly hours do not explain the difference and contribute to the unexplained portion of the decomposition. The sum of the ATECO components, possibly indicating alternative industry characteristics, also contributes to the explained component, yet it contributes more to the unexplained portion.

Table 5: Blinder-Oaxaca decomposition of gender wage differentials

Overall		
Male	7.223**	
Female	7.110**	
Difference	0.113**	
Explained	-0.008**	
Unexplained	0.122**	
N (male)	218,752	
N (female)	140,365	
Decomposition		
	Explained	Unexplained
Education	-0.044**	0.002**
Region	-0.004**	-0.016**
Type of contract	0.003**	-0.001**
Age	-0.003**	0.003**
Weekly hours	-0.022**	0.281**
Squared weekly hours	0.040**	-0.097**
Overtime	0.001**	0.000**
Evenings	0.003**	0.001**
Saturdays	-0.000**	0.005**
Work from home	-0.000**	0.001**
ATECO	0.017**	0.129**

** Denotes significance at the 1 % level.

4 Discussion

4.1 Impact of hours worked on the gender pay gap

From regressions on both data sets it is clear that industries matter when it comes to estimating income/salary and that women working for a particular industry explains a portion of the gender pay gap. This goes well with the suggested hypothesis of Blau and Kahn (2017) that occupation and industry effects play a relatively large role in estimating the gender pay gap. However, even though all of the industry characteristics considered (working overtime, evenings, Saturdays, and working from home) have an impact on income, not all of them necessarily impact the gender pay gap, too. For example, for this sample it does not seem to be true that flexible working arrangements have an impact on the pay gap as suggested by Chung and van der Horst (2020). Controlling for weekly hours worked decreased the magnitude of the negative impact of being female on income by more log points than the rest of the characteristics combined.

In particular, it is the shape of the wage-work-hour relationship that impacts the gender pay gap. In the estimations on the Labour Force Survey (the interval regression using squared hours and the MFP regressions), the shape of the curve is convex, indicating that there is a significant premium for the inconvenience of working overtime (Table 3). This relationship, combined with the fact that women on average work shorter hours and are less likely to work overtime (Table 1), is likely a contributor to the gender pay gap. This result is in line with Goldin's (2014) compensating wage differential theory where it is not necessarily the fact that women work fewer hours but the disproportionate rewards of working more hours that is at the root of gender pay gap in certain industries. While the salary estimations with respect to wages for the whole sample did not show the same inverse U-shape as in Wolf (2002) or Biddle and Zarkin (1989), it should be noted that the chosen sample did not include observations of worked hours below 18 or above 60 for which such relationship might exist.

Squared hours is also the greatest positive component of the explained part of the gender pay gap in the Blinder-Oaxaca decomposition (Table 5). Lastly, within-industry measures of disproportionate returns to overtime were the most significant predictors of the gender pay gap: industries where the hourly wage when working 50 hours exceeded the hourly wage when working 40 hours were associated with a significantly higher gender pay gap. Interestingly enough the same is not true for extreme overtime: the 40 to 60 hour wage ratio had the opposite effect on the gender pay gap. It is possible that these industries have relatively high employee substitutability. It should also be noted that the relationship between hours worked and wages differed between industries: for some industries hourly wages increased in hours worked, for some the relationship was more linear and for some a decrease was observed after a certain cut-off point. Accordingly for some of the industries the relationship indeed may resemble the aforementioned inverse U-shaped curve but not necessarily for the entire workforce.

The importance of non-linear wages in gender pay gap estimation suggests that better regulated overtime and improvements in substitutability of workers could be the way forward when it comes to solving the gender pay gap. Alternatively – a shift in women's roles as caretakers is needed to change their preferences for flexibility in work. However, it can be argued that all workers would rather benefit from more flexibility, not the other way around where women should be encouraged to pursue overworking. Lastly, better labour law controls could be implemented since a significant portion of the sample reported working more than the 48 hours set as the maximum working hours including overtime. In any case, the solutions have to focus on the "greedy" industries with increasing returns to working overtime.

4.2 Limitations and future research

Despite controlling for different individual and firm characteristics, industries (estimations on the LoSai data set), as well as their flexibility characteristics (estimations on the Labour Force Survey), a significant gender pay gap between 12 and 20 log points remains unaccounted for. Even more, it is unclear what kind of residual industry characteristics ATECO variables account for (possibly prestige, difficulty to break into the industry, difficulty of tasks, etc.). Also implementing more controls and dataset comparisons could shed light on the considerable differences in the gender pay gap estimations between data sets. Further research is necessary to account for the remaining unexplained gender pay gap in order to implement solutions.

So far research on the gender pay gap and industry flexibility has been relatively limited to a few countries. The findings are not necessarily applicable to others due to cultural norms and other country-specific considerations. Although it is likely that the same trends that apply in the US and Italy also are relevant for the eurozone, more research is needed to establish whether the same patterns wage-work-hour and gender pay gap patters prevail there as well.

5 Conclusions

The aim of this paper was to explore the relationship between industry flexibility and the gender pay gap. The convexity in the hours worked and income relationship in combination with women's tendency to work shorter hours was demonstrated to be the main mechanism behind the gender pay gap. Other industry flexibility characteristics played a small role, if any, in determining the gender pay gap. Further research is needed to account for the remaining gender pay gap and alternative industry characteristics behind the difference.

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