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Marliese Wolf BSc

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Digitalisation-Induced Wage Changes

A Decomposition Analysis Of Inequality Measures For Europe

Marliese Wolf

Abstract

Based on EU-SILC micro-level data, I determine the contribution of the rise in usage intensity of digital technology in the work context to wage inequality and the gender wage gap in recent years. Following the approach of previous research, I apply a 4-category task approach (Autor, Levy, and Murnane (2003)) to design proxies for the characteristics of occupations which capture technological change. The determination of the effects of various factors on the inequality measures is accomplished using a counterfactual decomposition methodology introduced by Fortin, Firpo, and Lemieux (2011). Evidence for a major role of digitalisation is provided. The implications are found to differ considerably between the sexes as well as along the wage distribution. While women at the left tail of the distribution experience negative consequences, the effect is negligible for female workers at higher wage-deciles. A strongly varying impact of task measures is entailed along the distribution for male workers. In general, the effect appears to be less inequality-promoting in the sample of men. Decomposing the gender wage gap suggests a discrimination-changing impact of technological change.

Contents

1 Introduction

Workers experience ever-evolving working environments and occupational tasks. Particularly, this process is characterized by the three Industrial Revolutions. Each marks an exceptional progress of mankind and was accompanied by fundamental transformations in the economy, labor market and workers working conditions. The First Industrial Revolution, taking place in the second half of the 18th century, facilitated mobility and transportation through the invention of the steam engine and the construction of railway networks. Subsequently, the introduction of the assembly-line production, which enabled mass production from the late 19th century onwards, characterized the Second Industrial Revolution. In the 1960s, the successive application of computers and, later, the internet initiated the Third Industrial Revolution, also known as the Digital Revolution. While at first the scope of usage of computers was limited, their employability widens as digital technology is becoming more and more sophisticated. Accordingly, the enhanced integration of computers and robots is accompanied by their rising influence on the surrounding environment.

Labor economists extensively study the impact of technological change on employment and wages; these changes result to be non-neutral, in fact, they are found to be one of the driving forces of the shifts in the employment structure and wages. Various ideas have been formulated to explain the observed labor market phenomena. The two mostly regarded hypotheses focus on the heterogeneous impact of technology on different types of labor.

Digital devices tend to replace routine jobs as machines possibly displace human labor in tasks that can be described as routine or identified as codifiable. This concept of technological progress is known as routine-biased technological change (Goos, Manning, and Salomons (2010)). Non-routine jobs are considered to be largely unaffected. Thus, mainly workers in the middle of the wage distribution are affected and consequently experience a decrease in their work demand, in comparison to high-skilled and low-skilled occupations. Goos, Manning, and Salomons (2010) provide evidence for the routine-replacing technological change hypothesis explaining wage polarization in the EU. While Autor and Dorn (2013) find, inter alia, a reallocation of labor activity away from routine tasks for US data.

The so-called skill-biased technological change hypothesis (see eg. Autor, Katz, and Krueger (1998) or Acemoglu and Autor (2011)) emphasizes that improvements in technology increase the relative demand for more skilled workers, as digital technologies are complementary to skills. This, in turn, raises returns to skills, e.g. measured by education, as well as employment in occupations that require abstract cognitive and problem-solving skills. Numerous empirical evidences exist for the skill-complementarity of technological change (see Akerman, Gaarder, and Mogstad (2015), Centeno and Novo (2014), Van Reenen (2011)).

Undoubtedly, the intensifying usage of new technologies in the workplace influenced the workers' wages and, as was shown by previous research, the effect is heterogeneous for different skill levels and occupational groups. These findings raise the question of how digitalization shaped society's wage inequality. The change in inequality in developed countries finds some leading explanations in economic literature, which addresses this topic through skill-biased technological change and ongoing globalization[1]. Both imply an increase in the relative demand for highly skilled workers, which causes a faster growth of their wages, thus enhancing wage differentials. However, globalization typically leaves unaffected the low-skilled service workers at the bottom of the wage distribution, while it entails an impact for the other skill levels.

Many economists see an explicit causal relationship between technological changes and the observed variation in wage inequality in the U.S. economy over the last decades. Firpo, Fortin, and Lemieux (2011) argue that technological change and offshorability are, among other factors like changing returns to education, driving forces in the alterations of the distribution of wages over the last three decades. This statement is supported by the findings of other prominent studies, such as the one of Autor and Dorn (2013). The two researchers conclude that routine-biased technological change contributed considerably to the decrease in bottom-end wage inequality and to the increase in top-end wage inequality in the US between 1980 and 2005.

[1]Empirical evidence of the implications of offshorability, which is often used as an equivalent of globalization, is provided by Oldenski (2014) for the US and Carluccio, Fougere, Gautier, et al. (2016) for France and Hummels et al. (2014) for Denmark as examples for European countries.

The movements of the distribution of wages in European countries differ greatly from the ones in the US. Only little empirical support exists for the presence of the phenomenon of wage polarization[2] in Europe. Some previous studies analyse the determinants of inequality change for single countries while little attention was directed towards studying the EU as a whole. Only a minority of the performed research had a particular focus on the impact of digitalization and the importance of technological progress in order to explain changes in wage inequality indicators. Naticchioni, Ragusa, and Massari (2014) investigate changes in wage and income inequality between 1996 and 2007 with respect to numerous covariates. They find no evidence of wage polarization for Europe. This result is in line with research performed on other European countries, e.g. Goos and Manning (2007) for the UK or Antonczyk, DeLeire, and Fitzenberger (2018) for Germany. Further, Naticchioni, Ragusa, and Massari (2014) observe a U-shaped impact of technological transformations along the wage distribution, which is especially pronounced in the lower tail of the distribution, hence indicating an important role on inequality changes through heterogeneous impacts along the wage distribution. The empirical evidence for related research questions mentioned so far includes only data before the year 2007. However, the spreading of digital technologies did not slow down or even stop thereafter. The year 2004 is assumed to have been the first year with more digital than analogue data. However, what has happened since then? What are the implications of the spread of new technologies for the labor market? How does the Digital Revolution affect wages and wage inequality?

The objective of this thesis is to decompose the decrease of wage inequality and explain the changing pattern of gender wage gaps in selected EU countries with particular focus on technological change. The task model, applied to the data using the O*NET dataset, approximates the exposition of occupational groups to the adaption of new technologies. I use the decomposition method proposed by Fortin, Firpo, and Lemieux (2011) to identify the respective contribution of each covariate to wage differentials.

Compared to related research, this thesis extends the period covered by the data to

[2]The term wage polarization describes the larger growth of wages in the bottom and top ends of the wage distribution relative to the middle. Usually it accompanies job polarization, the concentration of workers in high- and low-skill jobs.

more recent years. This allows for more up-to-date insights into the determinants of wage and wage inequality dynamics within this specific context. To my knowledge, I am the first one to decompose the gender wage gap in numerous European countries in recent years at multiple points of the wage distribution paying special attention to technological change. I further expand upon existing literature by separately considering the population of women in Europe and investigating the heterogeneous effect of digitalization and automation between the genders.

The decomposition results provide evidence for a substantial impact of technological change on inequality in hourly wage that differs along several dimensions. Overall, digitalization and the risen use of robots function inequality-increasing for the pooled sample of workers. While women at the top deciles are not negatively affected, female workers at the bottom of the wage distribution suffer particularly from the transformed working environment. On the contrary, technological progress has diverging implications for men. However, these effects are not dominant in the determination of the wage or wage inequality. The decomposition of the gender wage gap indicates the relevance of technological change for gender-based wage discrimination through the heterogeneous roles of the occupational task variables in the earlier $(2004 - 2006)$ and the later $(2014 - 2016)$ sample.

The remainder of the thesis will be structured in the following way: Firstly, the subsequent chapter provides a motivation for the used task model. Secondly, section 3 introduces the counterfactual decomposition methodology used to decompose wage inequality differentials into the respective contribution of each covariate. The differing levels of the gender wage gap across EU countries are briefly discussed in chapter 5. An overview of the used data is given in section 4. Before discussing the decomposition results in chapter 6, the application of the methods and the econometric specification are presented in section 3.3. Subsequently, the determinants of gender wage gaps are investigated and discussed using the examples of Austria and Italy in chapter 7. Lastly, chapter 8 offers a summary and a conclusion relevant to this research topic. Tables can be found in the Appendix.

2 The Task Model

For the purpose of investigating the sources of change in wage and wage inequality it is important to additionally to considering workers‘ formal education also understand the task content of occupations. Furthermore we need to take account of changes in the task content of occupations. A comprehension of what computers do and an awareness of the tasks that present computer technology is particularly suited to perform is substantial for the application of this approach. The task model offers a powerful approach for the analysis of changes in technology and how spreading globalization heterogeneously impact the workers' wages.

2.1 Occupational Task Measures as Proxies for Technological Progress

The rationale behind the task model is to construct direct measures of occupational skill requirements that are based on the activities people perform on the job. Hence, a major feature of the task model is the definition of each distinct occupation as a series of tasks. Tasks are part of the work process and defined as activities that individuals have to perform in a specific occupation to produce output. This concept enables the analysis of changes in the task composition of occupations directly.

Tasks can be distinguished according to whether they can be performed by capital (ICT and robots) or by human labor force only. Autor, Levy, and Murnane (2003), who first proposed this model, stated that present computer technology is particularly suited to performing tasks with a specified, clear pattern and codeable work steps. At this point, oriented at the seminal paper of Autor, Levy, and Murnane (2003), I want to present an example to illustrate which tasks are easily automatable and which ones are not at risk of being carried out by computers or robots: Taxi driving and assembling parts of a car are both considered as jobs performed by low-skill workers. However, at present, computers are able to take over a major share of the assembling process using suiting software and machines while they are not yet used for taxi driving. Similarly, playing chess and defending a client in court are both high-skilled tasks. While computers can easily perform the first task, current technology is not ready to complete the second one. These two instances explain better which tasks of a certain occupation can be performed by a computer. The observation that tasks cannot be digitalized unless they are codifyable procedures is key to the original version of the task approach. This suggested conceptualization of occupations enables the quantification of the degree to which it is possible to automate an occupation.

Occupations are defined as a combination of the three following task categories: The first group includes tasks requiring the ability to think creatively or critically, solve problems autonomously or communicate decisions within the workplace context. These tasks are denoted as *abstract*, or analytic, tasks. Secondly, any interactive activities that are functions requesting social and interpersonal skills and include working in teams and cooperating with other people as much as selling are denoted as *service* tasks. All tasks which are characterized by repetitive activities with a regular pattern are called *routine*. The first two categories can be summarized under the term *non-routine*. An occupation requires the worker not only to perform one task category but, although at different levels of intensity, all three. The categorization of variables in routine and non-routine (abstract and service) is key to the interpretation. This distinction allows for a measurement of the routine-task share of an occupation and thus a determination of the possibility to automate it. Jobs with a higher routine-task intensity are also more likely to face substitution of human labor force by computer capital. Apart from the substitution of routine task workers, digital technology appears complementary to non-routine tasks, both analytic and interactive, as ICT and robots increase the productivity of employees performing those tasks.

An effect of the ongoing digitalization process is a change in task content of an occupation over time. A worker employed in a specific job may need to drop, pick up, intensify or reduce the accomplishment of certain tasks over time. Skill requirements and skill composition evolve due to digitalization. This feature of digital transition as well as the ongoing spreading of technologies is captured by the task approach of occupations as the model does not only take the extent of ICT usage but also the intensity into account.

The consequences of the adoption of new digital technologies impacts the tasks of the various occupation groups heterogeneously. Therefore, digitalization also influences the between-occupational changes of task measures. The task model incorporates this feature through observing changes in skill requirements within occupations. This is made possible as the occupational classifications and variables used to construct the task measures are held constant over time while the intensity of the skill usage varies. This way of constructing the technology proxies for the analysis allows me to follow changes in the intensity of digital technologies on the workplace. Changes in the wage structure within and between occupations should be linked to the combination of tasks performed in these occupations. In conclusion, the task content of occupations appears as a useful predictor for changes in both the level and dispersion of wages across occupations that can be explained by technological progress.

However, the task approach does not prove to be the optimal method to solve measurement problems of task content of occupations in all respects. Assigning tasks to occupations leaves aside the heterogeneity in job tasks among individuals within an occupation. Individual worker skills and actual job tasks are not common to all workers within an occupation. Therefore, the occupation-level task approach developed by Autor, Levy, and Murnane (2003) and applied in this thesis shall only be considered as a rough approximation to the microeconomic assignment process. The computation process of the task measures included in the empirical analysis is presented in section 4.4.

2.2 Accompanying Technological Progress: The Impact of Globalization

Besides the share of automatable tasks in an occupation, it is important to consider further factors shaping wages that are also triggered by technological advancements. Offshoring is such a determinant. The same reasoning used for digitalization can be applied to the process of offshoring. If the economic costs of offshoring due to increased mobility in the modern world or substitution through technological capital are smaller than the cost of employing domestic labor force, the domestic worker will be dispensable.

According to Blinder and Krueger (2013) there exist two important criteria for non-offshorability: the need for a job to be performed on-site and the requirement of face-to-face interactions in that job. Some tasks, like sewing together fabric parts to a T-shirt, are far more suitable to offshoring than others, eg. health care. Therefore, it seems natural to apply an approach similar to the one for the construction of technological proxies to compute the offshoring potential of an occupation.

Goos, Manning, and Salomons (2010) find that there is a decreased demand for jobs that are identified as offshorable. This observation brings along arguments for a worse wage bargaining position of workers in the affected occupations. However, the worse bargaining position not necessarily results in a reduction of absolute wages. Yet, unaffected jobs are likely to experience a higher rise in salary. This may drive up wage inequality if the occupations threatened by offshoring lie in the lower part of the wage distribution. If offshoring has the expected effect on wages, leaving this variable out of the regression analysis could also lead to incorrect estimates of the coefficients of technology measures. However, other research provides estimated effects of offshorability on wages pointing in the other direction. Carluccio, Fougere, Gautier, et al. (2016) find a wage-increasing impact of offshoring. These results are supported by theoretical predictions suggesting that productivity-rising effects of offshoring exceed the negative ones (ie. the substitution of domestic workers). Hummels et al. (2014) show for Denmark that offshoring has heterogeneous effects across the different skill- and education-levels.

3 Chapter: Decomposition Method

The decomposition method introduced in this chapter generalizes the Oaxaca-Blinder (O-B) decomposition method to applications for non-linear functionals. It was proposed first by Fortin, Firpo, and Lemieux (2011) and will be referred to as FFL approach, corresponding to the authors' initial letters, henceforth. Within the context of this thesis, the application of the FFL method permits a detailed understanding of the sources of changes in wage inequality measures. In particular, I will use this decomposition method to identify the impact of each included covariate on the changes in general wage inequality measured by interquartile ranges as well as on the gender wage gap at all deciles and quartiles of the wage distribution. The approach is a two-stage method to break down alterations in the distribution of an outcome variable. In the first step, the distributional statistics of the re-weighted samples are broken down into a wage structure and a composition effect. This process is also known as the aggregate decomposition. The wage structure effect captures the changes in returns to covariates between the two groups while the composition effect is related to inter-group changes in the distribution of these covariates. As an illustrative example consider a worker who earns 8 EUR per hour on day one and 10 EUR per hour on day 2. The increase in wage arises from one (or both) of the above described effects. In case the worker's education level rises from completed secondary education to a university degree between the two days, then, ceteris paribus, the composition (or endowment) effect captures the observed change. If the worker's education as well as his/her other characteristics remain unchanged between the two points in time, the wage rise is attributed to change in the wage function. Indeed, both forces usually occur simultaneously. Thus, the objective is to disentangle the two effects.

In a second stage a so-called detailed decomposition is conducted. It identifies the contribution of each covariate to the two effects determined above. The detailed decomposition is carried out using the re-centered influence function (RIF) regression method introduced by Firpo, Fortin, and Lemieux (2009). This chapter is based on Firpo, Fortin, and Lemieux (2018).

3.1 Identification of the Counterfactual Distribution: A Reweighting Approach

The first stage decomposes the overall change in the distributional statistic ν between two groups $T = 0$ and $T = 1$ into a wage structure effect and a composition effect. The overall wage gap, computed as the difference in ν between the two groups, denoted as Δ_O^ν, can be segmented into the two effects in the following manner:

$$\begin{aligned}
\Delta_O^\nu &= \nu(F_{Y_1|T=1}) - \nu(F_{Y_0|T=0}) \\
&= \nu(F_{Y_1|T=1}) - \nu(F_{Y_0|T=1}) + \nu(F_{Y_0|T=1}) - \nu(F_{Y_0|T=0}) \\
&= \underbrace{(\nu_1 - \nu_C)}_{wage\ structure\ effect\ (\Delta_S^\nu)} + \underbrace{(\nu_C - \nu_0)}_{composition\ effect\ (\Delta_X^\nu)} .
\end{aligned}$$

The expression $F_{Y_t|T=s}$ denotes the conditional actual wage distribution in period t for $s, t = 0, 1$ and $s = t$. The distributional statistic ν (e.g. the quantiles of the wage distribution $q_\tau = Q(F, \tau)$) is expressed as a functional [3] of the conditional wage distribution ($\nu(F)$). Key to the underlying decomposition method is the counterfactual distribution $F_C = F_{Y_0|T=1}$. The counterfactual is defined as the distribution which would have prevailed if workers with the characteristics observed in period 1 would have been paid under the wage structure of period 0. This additional distribution can be obtained by changing the distribution of characteristics of the observations through reweighing using the factors given by eq.(1) while keeping the conditional distribution of wages unchanged.

While the conditional distribution of $Y_1 \mid T = 1 \sim F_1$ and $Y_0 \mid T = 0 \sim F_0$ can be non-parametrically identified from the data, the estimation of the counterfactual distribution poses a challenge. As a proposal for solution, Lemieux (1996) suggest a semi-parametric approach: a reweighting of the data using inverse probability weights. Precisely, the counterfactual distribution F_C is estimated based on the reweighted data of period 0 which then has the same distribution of observables as in period 1. The parameters of the counterfactual distribution are identified if the assumptions of ignorability and overlapping support hold. In the present case, ignorability refers to the distribution of unobserved determinants ϵ of the wage being independent of the group T given the vector of observable characteristics $X = x$. The ignorability assumption ensures that there no selection into groups based on unobservables takes place. The assumption of overlapping support demands that no value of observable characteristics is only observed among individuals of

[3] A functional is a mapping of a vector space of functions on the set of real numbers: $\nu : F \to \mathbb{R}$.

one group. Technically expressed, this assumption requires that for all possible values x of X, $p(x) = Pr[T = 1 \mid X = x] < 1$. The identification of the counterfactual distribution $F_C = F_{Y_0|T=1}$ subsequently allows for the identification of $\nu(F_C)$. Consequently, if the two assumptions hold and thus the counterfactual distribution is identified, then the wage structure and the composition effect are identifiable from the data.

For the reweighing of distributions, the factors are given by the following three functions:

$$\begin{aligned}
\omega_1(T) &= \frac{T}{p} \\
\omega_0(T) &= \frac{1-T}{1-p} \\
\omega_C(T,X) &= (\frac{p(X)}{1-p(X)}) * (\frac{1-T}{p}).
\end{aligned} \tag{1}$$

The reweighing functions ω_1 and ω_0 transform features of the marginal distribution of Y into features of the conditional distribution of Y_1, given $T = 1$, and Y_0, given $T = 0$. The third reweighing function, ω_C, transforms features of the marginal distribution of Y into features of the counterfactual distribution: $Y_0 \mid T = 1 \sim F_C$.

3.2 RIF Regressions and Decomposition

The primary objective of this decomposition analysis is the determination of the respective contributions of each covariate to Δ_S^ν and Δ_X^ν. Fortin, Firpo, and Lemieux (2011) state that for distributional statistics ν other than the mean, the decomposition can be conducted similarly to the OB decomposition of the mean if recentered influence function (RIF) regressions are used. A RIF regression is a standard regression with the RIF of the statistic of interest (RIF(Y;ν,F)) as the dependent variable. The RIF of ν is, expressed simply, obtained by re-adding the distributional parameter ν to the influence function (IF)[4]:

[4]The influence function measures the impact of each observation on the distributional parameter. In the context of this thesis, the IF determines the reaction of the distributional statistic $\nu(F)$ to a marginal change of the wage distribution F at wage y. The definition of the influence function is the following: $IF(y;\nu,F) = \lim_{\epsilon\to 0} = \frac{\nu(F_\epsilon)-\nu(F)}{\epsilon}$ where $F_\epsilon(y) = (1-\epsilon)F + \epsilon\delta_y$. F represents the empirical distribution function $\tilde{F}(x) = \frac{1}{N}\sum_{i=1}^{N} \not\Bbbk(x_i \leq x)$

$$RIF(y;\nu,F) = IF(y;\nu,F) + \nu(F).$$

While the influence function has a mean of zero by construction, the expected value of the recentered influence function equals the distributional statistic ν. Accordingly, the distributional statistics can be written as expectations of the RIF:

$$\nu_t = \mathbb{E}[RIF(Y_t;\nu,F_t)|T=t] \ for\ t=0,1 \quad and \quad \nu_C = \mathbb{E}[RIF(Y_0;\nu,F_C)|T=1].$$

Using the specification of the conditional recentered influence function and applying the law of iterated expectations, the distributional statistic ν can also be expressed by the following term:

$$\nu(F) = \int \mathbb{E}[RIF(Y;\nu,F)|X=x]\ dF_X(x).$$

In a general form, the RIF-regressions can be written as

$$m_t^\nu(x) = \mathbb{E}[RIF(Y_t;\nu_t,F_t)|X,T=t],\ t=0,1;$$
$$m_C^\nu(x) = \mathbb{E}[RIF(Y_0;\nu_C,F_C)|X,T=1].$$

For simplicity the case of a linear specification of the RIF regression is considered henceforth. The linear projections of the recentered influence function onto the covariates

$$m_{t,L}^\nu(x) = x'\gamma_t^\nu \quad and \quad m_{C,L}^\nu(x) = x'\gamma_C^\nu$$

are used, where γ_t^ν and γ_C^ν are the vectors of the corresponding regression coefficients.

The effects of a change in the distribution of characteristic X_k between group T = 0 and group T = 1 on the distributional statistic ν of the *reweighted* sample[5] can be denoted as

$$\Delta_X^\nu = \sum_{k=1}^{K}(\mathbb{E}[X_k \mid T=1] - \mathbb{E}[X_k \mid T=0])'\gamma_{0,k}^\nu.$$

[5]The sample means thus correspond to: $\bar{X}_t = \sum_{i=1}^{N}\hat{\omega}_t(T_i)X_i$ where $t=0,1,C$.

The effects of a change in the return to characteristic X_k between group T = 0 and group T = 1 on the distributional statistic ν of the *reweighted* sample can be denoted as

$$\Delta_S^{\nu} = \sum_{k=1}^{K} \mathbb{E}[X_k \mid T = 1]'(\gamma_{1,k}^{\nu} - \gamma_{C,k}^{\nu})$$

If linearity is assumed and this specification only holds locally, the decomposition results are biased. For this case, Firpo, Fortin, and Lemieux (2018) propose a solution involving both reweighing and RIF-regressions. The combination of the two tools enables the computation of consistent estimates of the counterfactual mean $\bar{X}_C$ and the counterfactual coefficients γ_C from the RIF-regression on the re-weighted sample. This approach assures that, under ignorability, each decomposition term will only reflect either the differences in wage structures or in the covariates distribution, but never both. The true wage structure effect, which is the one uninfluenced by differences in the distribution of observable characteristics X between the two groups investigated, therefore reflects the true change in the wage structure. Rewriting the *reweighted* wage structure effect, $\Delta_{S,R}^{\nu}$, gives

$$\Delta_{S,R}^{\nu} = \underbrace{\bar{X}_1[\gamma_1^{\nu} - \gamma_C^{\nu}]}_{\Delta_{S,p}^{\nu}} + \underbrace{(\bar{X}_1 - \bar{X}_C)\gamma_C^{\nu}}_{\Delta_{S,e}^{\nu}}$$

composed of the *pure* wage structure effect, $\Delta_{S,p}^{\nu}$, and the reweighting error, $\Delta_{S,e}^{\nu}$.

Similarly, the *reweighted* composition effect,$\Delta_{X,R}^{\nu}$, is expressed by the sum of the *pure* composition effect,$\Delta_{X,p}^{\nu}$, and the specification error,$\Delta_{X,e}^{\nu}$

$$\Delta_{X,R}^{\nu} = \underbrace{(\bar{X}_C - \bar{X}_0)\gamma_0^{\nu}}_{\Delta_{X,p}^{\nu}} + \underbrace{\bar{X}_C[\gamma_C^{\nu} - \gamma_0^{\nu}]}_{\Delta_{X,e}^{\nu}}.$$

The estimate provides a first-order approximation of a change of the distribution of X on ν. This fact and the possibility that the RIF-regression is, contrary to the used specification, not actually linear contribute to the approximation (or specification) error. The specification error $\Delta^{\nu}_{-,e}$ captures the difference between the by reweighting estimated effect $(\Delta^{\nu}_{-,R})$ and the effect obtained from a linear approximation using the RIF-regression $(\Delta^{\nu}_{-,p})$. The magnitude of the error indicates the appropriateness of the RIF-regression-based specification.

If the ignorability assumption holds, the results can be interpreted causally. This applies especially for the wage structure effect.

3.3 Empirical Specification

To analyze the data, I use the following empirical model:

$$\widehat{Pr}_i\{group\} = \alpha + \beta X_i + \delta\big[Exper \times Educ\big] + \epsilon_i \tag{2}$$

$$\widehat{RIF}(y, q_{\tau t}, F) = q_\tau + \widehat{IF}(y; q_\tau, F) = q_\tau + \frac{\tau - \mathbb{I}\{y \leq q_\tau\}}{f_Y\{q_\tau\}} \tag{3}$$

$$\widehat{RIF}(y, q_{\tau t}, F) = \mu + \gamma_t X_i + \kappa D_l + \lambda C_j + \xi_{ijt} \tag{4}$$

$$\hat{\Delta}^{\nu}_{S,R} = \left(\sum_{i=1}^{N} \hat{\omega}_1(T_i)X_i\right)'[\hat{\gamma}^{\nu}_1 - \hat{\gamma}^{\nu}_C] + \left(\left(\sum_{i=1}^{N} \hat{\omega}_1(T_i)X_i\right) - \left(\sum_{i=1}^{N} \hat{\omega}_C(T_i)X_i\right)\right)'\hat{\gamma}^{\nu}_C \tag{5}$$

$$\hat{\Delta}^{\nu}_{X,R} = \left(\left(\sum_{i=1}^{N} \hat{\omega}_C(T_i)X_i\right) - \left(\sum_{i=1}^{N} \hat{\omega}_0(T_i)X_i\right)\right)'\hat{\gamma}^{\nu}_0 + \left(\sum_{i=1}^{N} \hat{\omega}_C(T_i)X_i\right)'[\hat{\gamma}^{\nu}_C - \hat{\gamma}^{\nu}_0] \tag{6}$$

Eq.(2) estimates the conditional probability of being in group 1. This is the probability that an individual i is in group 1 given i's personal characteristics as well as i's occupation's characteristics measured by task variables and sector dummies, all contained in X_i.[6] Additionally, this probability is a function of a set of interaction terms to increase the specification's flexibility. $Exper \times Educ$ captures the experience - education interaction. The predicted probability is used to compute the reweighting factors as stated in section 3, eq. (1). Next, eq. (3) demonstrates the computation of the recentered influence function (RIF)

[6] The explanatory variables are described in detail in section 4.

for the τ-th quantile of the wage distribution F of group t. Eq.(4) defines the recentered influence function (RIF) regression, a linear regression where the usual dependent variable is replaced by the estimated value of the RIF. Besides the individual and occupational characteristics, also year dummies (D_l) as well as country dummies (C_j) are included in the regression. Lastly, Eq.(5) and (6) determine the elements of the actual decomposition. The equation consists of two main components: the vector of coefficients γ_t estimated in eq. (4) and the weighted average of the covariates X_i, $\bar{X}_t = \sum_{i=1}^{N} \hat{\omega}_t(T_i)X_i$ where $t = 0, 1, C$.

4 Data

The empirical analysis of the dynamics of gross hourly wages is based on micro-level data for the population of selected European countries. The primary focus of this thesis lies on the effects of digitization where technological progress is included in the estimation using occupational task measures as proposed by Autor, Levy, and Murnane (2003). A motivation for this approach is provided in chapter 2. A detailed description of the computation of the task variables and the underlying dataset O*NET will be given in subsection 4.4 of this chapter. In addition, the contribution of several other possible explanatory factors for changes in the wage distribution are considered. These variables are taken from the European Union Statistics on Income and Living Conditions (EU-SILC), a microeconomic dataset from Eurostat.

4.1 Micro Data: EU-SILC

The EU-SILC is a database providing comparable information on measures of income and poverty as well as workers' characteristics like education, working experience and occupation for European countries. Data collection for this annual dataset has started in 2004. The analysis of the impact of digitalization on gross hourly wages is based on the EU-SILC waves of 2004, 2005, 2006, 2014, 2015 and 2016.

The EU-SILC database provides information on current gross monthly earnings of employees (variable PY200g) from which gross hourly wage can be derived by applying the following formula:

$$gross\ hourly\ wage = \frac{PY200g \cdot \frac{12}{52}}{PL060}$$

where PL060 indicates the hours worked per week in the main job under usual circumstances. The wage is adjusted for inflation using the annual average version of the harmonized consumer price index (HCPI) for each country[7]. The following covariates are considered in the analysis:

- Worker characteristics: experience, gender/marital status[8]
- Job characteristics: contract type, part time
- Education
- Sector
- Technology and offshorability[9]

Except for work experience, all covariates are included in form of dummy variables. *Work experience* is determined by the EU-SILC variable PL200 indicating the number of years spent in paid work. For observations with missing values of this variable a measure of potential labor experience serves as a substitute. Potential labor experience is defined as the difference between age (computed from PB010 (year of survey) and PB140 (year of birth)) and the variable PL190 (age when person started first regular job).

The dummy *female* is based on the information about the respondent's sex in variable PB150. The indicator for *marital status* equals 1 if the variable PB190 (describing the respondent's marital status) implies that the person is married ($PB190 = 2$).

Another important covariate is the *type of contract* an employee has. Taking contract duration (variable PL140) into account a dummy for the individual's employment was created in order to distinguish between permanent and temporary jobs. A *part time* worker

[7] The data can be downloaded from the Eurostat homepage: https://ec.europa.eu/eurostat/web/hicp/data/database

[8] The dummy *female* is not used in the analysis of the gender pay gap or the gender-specific wage growth. For these cases a dummy variable for marital status is included in its place.

[9] For the definition of these variables see section 4.4.

is identified by the measure of usual working-hours per week. If PB060 is smaller than 30, the job is categorized as being part time.

The classifications for education level, industry sector and profession differ between earlier (2004-06) and later (2014-16) years. As the data is indicated at different levels of aggregation, some adjustments are required to increase the classifications' comparability across periods. Even after regrouping some of the categories, occupations and industries remain partly incomparable between the two periods. For a detailed listing of the classifications see Appendix Tables 18 and 19. Otherwise, the definitions of the variables are mostly comparable over time.

The individual characteristic *education level* contains one out of six levels describing the highest educational attainment. According to their highest *International Standard Classification of Education* (ISCED) level achieved, this indicator distinguishes between respondents with primary, lower/upper secondary and post-secondary/tertiary education.

The workers' occupations stated in terms of the 2-digit *International Standard Classification of Occupations* (ISCO) (variable PL050 and PL051) play a major role. However, this variable is only included indirectly in the analysis as it is used to match the task and offshorability measures to the corresponding occupation. I discriminate between 22 occupations (see Appendix Table 18).

Industry sectors are defined according to their *Statistical Classification of Economic Activities in the European Community*, short NACE. These follow the NACE Rev. 1.1 for the earlier period and the NACE Rev. 2 for the later period. The applied categorization of industries corresponds to the most disaggregated level possible for a combination of the respective variables in the EU-SILC (PL110 (available for the years $2004-2006$) and PL111 (available for the years $2014-2016$)).

4.2 Sample Construction

For the analysis I restrict the original dataset to those observations for which a computation of hourly wage is possible. Due to the requirement of overlapping support for the two groups, only citizens of countries for which EU-SILC data exists in the first and second period can be considered. This restricted the dataset to four EU countries: Austria, Italy, Poland and Portugal. Another requirement for the observations incorporated in the analysis is the individual's labor market participation throughout the entire year. Thus, observations for which any kind of non-participation in the labor market over the year is indicated (Unemployment (PL080), Retirement (PL085), Studying (PL087) or Other Inactivity (PL090)) are not considered. Further, only individuals for which the full set of characteristics is available are included. To inhibit bias due to extreme values of reported wage, observations with a recorded hourly remuneration of less than 1 Euro are excluded from the sample. Also outliers at the right tail of the wage distribution are deleted with respect to the survey year as well as gender and country. Additional requirements for the individuals incorporated in the sample for the analysis are a minimum of 5 hours worked per week just like an age between 15 and 65 years. This results in a dataset with a total of 174,546 observations.

4.3 O*NET database

The US Occupational Information Network (O*NET) database, collects information on several hundreds of jobs categorized by the Standard Occupation Classification (SOC). The O*NET database is promoted by the U.S. Department of Labor/Employment and Training Administration and the successor of the Dictionary of Occupational Titles (DOT).

O*NET is based on the content model which rates occupations along different dimensions and identifies the most important types of information required about jobs. For each occupation there exists a range of standardized job descriptors providing information on personal, job and experience requirements, the individual's characteristics and the labor market situation for this occupation group. Within these categories, detailed indicators exist describing diverse facets of the job. For all properties an assessment of this attribute based on its importance, level or both is provided. For the thesis O*NET serves as source of information for the task content of occupations.

4.4 Construction of the Occupational Task Measures

Based on the work of Autor, Levy, and Murnane (2003), I merge job task requirements from O*NET data for the years 2004, 2005, 2006, 2014, 2015 and 2016 to create measures for the different task components of an occupation. This method is probably the least subjective approach to measure task content of occupations established so far by the literature. For the construction of the task indices I use selected variables of the categories regarding skills, abilities, work activities and work context. The selected variables are then allocated to one of the three categories:

- abstract tasks (e.g. critical thinking or instructing)
- service tasks (e.g. selling or negotiating)
- routine tasks (e.g. calculating or monitoring)

The exact O*NET occupational task content measures included in each of the three constructed task measures as well as the offshorability variable are listed in Table 20.

The task variables are determined by a two-step computation procedure.

Step 1: Computation of task measures

For the actual computation of the task variables an importance scale indicated for each variable on O*NET is used. The importance scale I quantifies the degree of relevance of that particular descriptor for a given occupation from 1 ("Not important") to 5 ("Very important"). This scale is available for all four data categories I use. Each task index is calculated by taking a simple mean of the z descriptor variables included:

$$task\ measure = \frac{1}{Z}\sum_{z=1}^{Z} I_z$$

The result is an occupational task measure for each occupation defined by the O*NET-SOC classification.

*Step 2: Match O*NET-SOC to 2-digit ISCO*

A major challenge is to match the occupation classifications which are distinct between the O*NET database and the EU-SILC dataset. The classification used by O*NET is the Standard Occupational Classification (SOC) on a 6-digit level while the EU-SILC indicates occupations by the International Standard Classification of Occupations (ISCO) on a 2-digit level for this purpose. To cope with this challenge, I use a matching process with two separate steps.

First, the O*NET-SOC-10 definitions, for the later years, (O*NET-SOC-00, for the earlier years) have to be combined with the 4-digit ISCO-08 (ISCO-88) classification system. For this purpose the crosswalks[10] between the two classifications provided by the U.S. Bureau of Labor Statistics and the Institute of Structural Research are used. Doing this, each O*NET occupation is mapped to an ISCO occupation where several O*NET occupations can be assigned to the same ISCO category. This is due to the used 2-digit ISCO classification being much more aggregate than the provided 6-digit SOC definition. In this substep simple means of task measures from O*NET level are taken to create a task measure for the 4-digit ISCO level. Then the new occupations classified by ISCO collapse from a 4-digit unit group to the aggregation level of the 2-digit sub-major group level which are then used for the analysis.

Like Firpo, Fortin, and Lemieux (2011) I calculate an offshorability index, the measure indicating the offshoring potential of an occupation, based on O*NET variables measuring direct interpersonal interaction (ie. face-to-face contact) or physical presence at the work location (ie. on-site job). The calculation method is the same as for the technological proxies above, except for one step that is added: the computed variable needs to be reversed so that it measures offshorability instead of non-offshorability.

For every year analyzed in the empirical section, I compute a separate value of the

[10]The crosswalk between ISCO-08 and SOC-10 can be downloaded at the official homepage of the Bureau of Labor Statistics: https://www.bls.gov/soc/ISCO_SOC_Crosswalk.xls. The crosswalk between ISCO-88 and SOC-00 can be downloaded from the homepage of the Institute for Structural Research: http://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/.

task measure. Hence, distinct sets of indices are created. While the variables included in computation of task measures are held constant the importance scale values might vary over time. Alterations capture changes in occupational tasks and skill requirements. This variation occurs due to technological advancements on the workplace or modifications in the offshoring possibilities following globalization and technological progress. The unmodified combination of included descriptor variables assures comparability between years. Further, the task measures do not vary between countries. This implies the assumption that the level of digitalization and automation as well as ongoing technological change are similar in all countries in the sample.

A table presenting the level of each task variable by occupation can be found in the Appendix (Table 3). The evolution of mean task measures across time is shown in Table 4. Abstract and service task importance increase considerably between the earlier and later years. Throughout the time period the change in routine task importance is not as large in magnitude. In particular this applies to the sample of women. In line with expectations, a decrease of this task type is observed. The table shows a sharp reduction in the importance of offshorability for almost all occupational groups.

4.5 Descriptive Statistics

The empirical analysis of overall wage inequality focuses on changes measured by differences in the 75-25, 75-50 and 50-25 interquartile ranges between $2004-2006$ and $2014-2016$. Before looking at a first decomposition of the change in log of hourly wage, I want to examine some basic features of the dataset and analyze the change in characteristics of the pooled dataset between the first period (containing data from 2004 to 2006) and the second period (covering the years 2014, 2015 and 2016). Table 1 presents the sample means by gender for the included covariates as well as the occupations at the used aggregation level. The means are computed using sample weights.

Over the underlying time period the labor market experiences some considerable changes: workers become more educated and experienced. The share of low-level education as the highest achieved education falls while the categories of secondary as well as tertiary education increase by up to 11.9%. Thus, it is possible to speak of an educational upgrading of the population of Austria, Italy, Poland and Portugal between 2004 and 2016.

A trend widely observed across industrialized nations is also present in the considered countries: a relative decrease in permanent workplaces and thus, an increase in temporary contracts.

Another noticeable property is the growth of the service, R&D and IT sector, incorporating the NACE industries J & K for Rev 1.1 or J & K & L-N for Rev. 2., while the manufacturing industries experience a fall in labor market share.

Of particular importance for the model are the task variables. Table 3 gives an overview of the task measures by occupation and period. This summary illustrates the relative greater importance of abstract tasks for high-skill professions as well as the higher focus on routine tasks in low-skill occupations. Service tasks measures which require interaction and interpersonal skills are highest in the occupational groups of teaching, health and service.

Now, it is also interesting to investigate how occupational tasks are correlated with the mean wage in the respective profession. Figure 1 depicts the correlation between routine-task intensity (RTI) and mean wage of the occupation group. Routine-task intensity of a job is computed as the relative importance of routine-tasks compared to tasks classified as non-routine (service and abstract). A distinct negative correlation between RTI and the mean of the hourly wage is evident in the graph. Another relevant property is the decrease of RTI, and thus a fall in the relative importance of routine work compared to other tasks, over time.

The variable that serves as the dependent variable in the analysis is the log of gross hourly wages. A more detailed description of the change in log hourly wages is given in Figure 2. The graph shows the log wage differentials between $2004-2006$ and $2014-2016$ by percentile for each country included in the dataset. In general, the left tail of the wage distribution exhibits large changes in log hourly wage while the variation is more moderate in the right tail. This does not hold for the example of Italy where the reverse occurs.[11]

[11] I performed several checks of the pattern of change in hourly wages in Italy using different calculation

Figure 1: Routine-Task Intensity vs. Mean Hourly Wage by Occupation

(a) 2004-2006 (b) 2014-2016

Source: Author's own representation based on EU-SILC and O*NET data.

The evident differences in wage changes indicate an overall decrease of wage inequality that is mainly based on the considerable decrease of the 50-25 interquartile range. Figure 2 gives further insight into wage growth by gender. Generally, the differences in wage growth between men and women partially seem negligible although there exist variations over the wage distribution as well as by country. The respective determinants, however, may diverge considerably.

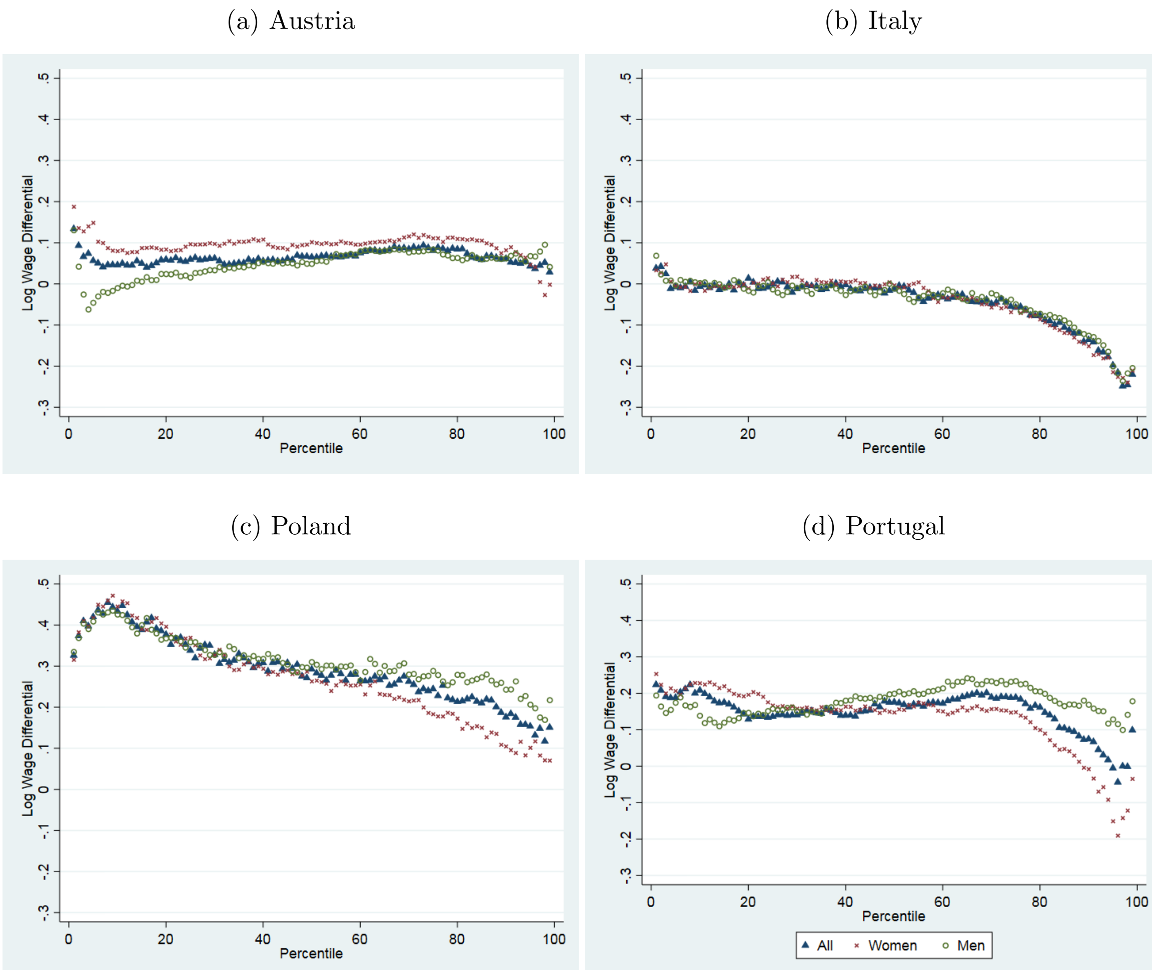
Table 6 confirms the expected phenomenon of decreasing low-end wage inequality. A rise in upper-end wage inequality is found. However, Figure 2 indicates that the chosen inequality measures (ie. the 75-25,75-50 and 50-25 gap) do not fully capture wage dynamics. The respective changes would be more pronounced if the interquartile ranges were widened.

5 Gender Wage Gap

Inequality is not only present in form of a spread of the remuneration of workers between occupations but also comprises gender-based wage differentials. The gender wage gap is a widely studied phenomenon. Even though a lot of research has been conducted on this topic,

methods and underlying income. Similar structures of wage development were found for all definitions.

Figure 2: Change of Gross Hourly Wage by Percentile (2004-2006 to 2014-2016)



Source: Author's own representation based on EU-SILC data.

not all causes and drivers have yet been sufficiently considered. Within the context of this thesis, the importance of technological progress as a determinant of the gender-based wage discrimination is an interesting aspect to investigate. Here, the open question is whether the role of new technologies is changing over time for the determination of the gender wage gap.

Black and Spitz-Oener (2010) find that a decrease in routine tasks for women relative to men combined with an increase in non-routine abstract and interactive tasks account for a considerable fraction of the reduction in the gender wage gap in West-Germany. In parts, Black and Spitz-Oener (2010) trace back these task changes to technological progress. A paper of Christl and Köppl-Turyna (2017) analyzes the role of numerous skills and tasks for the gender wage gap in Austria. Including these additional controls reduces the unexplained gender wage gap considerably compared to other studies. Their result indicates that gender-differences in worker skills are an important determinant of the gender wage gap. This motivates the decomposition of gender wage gaps with respect to technology-linked task measures. The corresponding detailed decomposition results will be discussed in section 7.

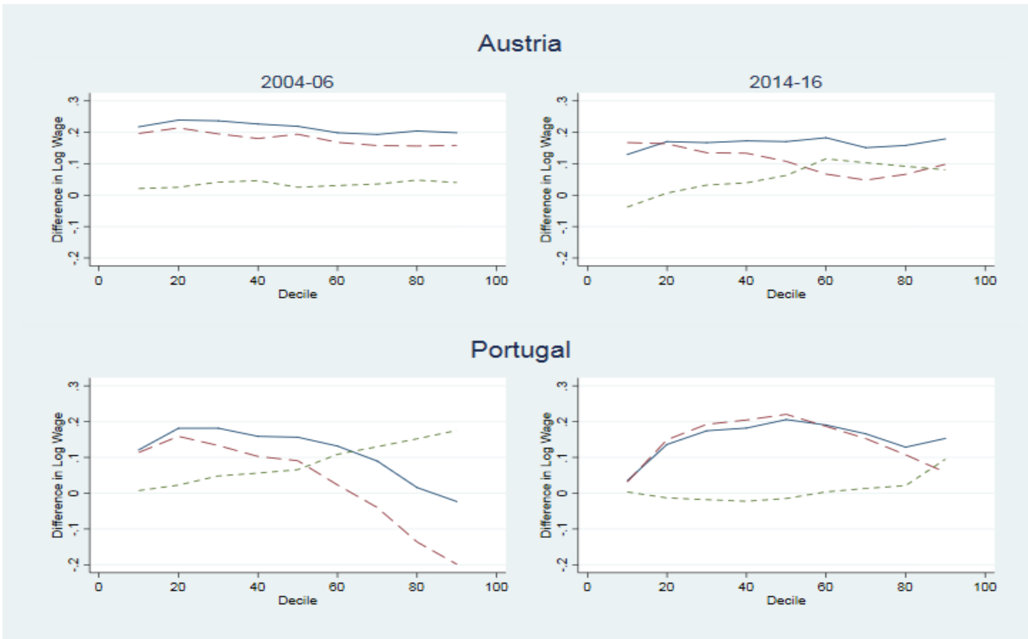
Gender pay gaps exhibit different patterns and magnitudes across countries and within a country along the wage distribution. This is illustrated in Figure 3 where the gender wage gap in four analyzed countries in the beginning ($2004-2006$) and the end ($2014-2016$) of the covered time span are depicted. Austria and Portugal serve as examples for countries with high differences in wages between women and men. Italy and Poland exhibit considerably smaller gaps in gross hourly wages between the genders.

In the earlier period, $2004-2006$, the gender pay gap in Austria is on average above 20%. Even though it decreases over the following 10 years, the gap remains at an comparatively high level (above 15%). Also the pattern changes over time. In $2004-2006$ the gender-differences in wage exhibit a falling trend along the wage distribution with the largest wage gap being evident at the 2nd decile. In recent years, the gender wage gap particularly small divergences occur in the 7th and 8th decile.

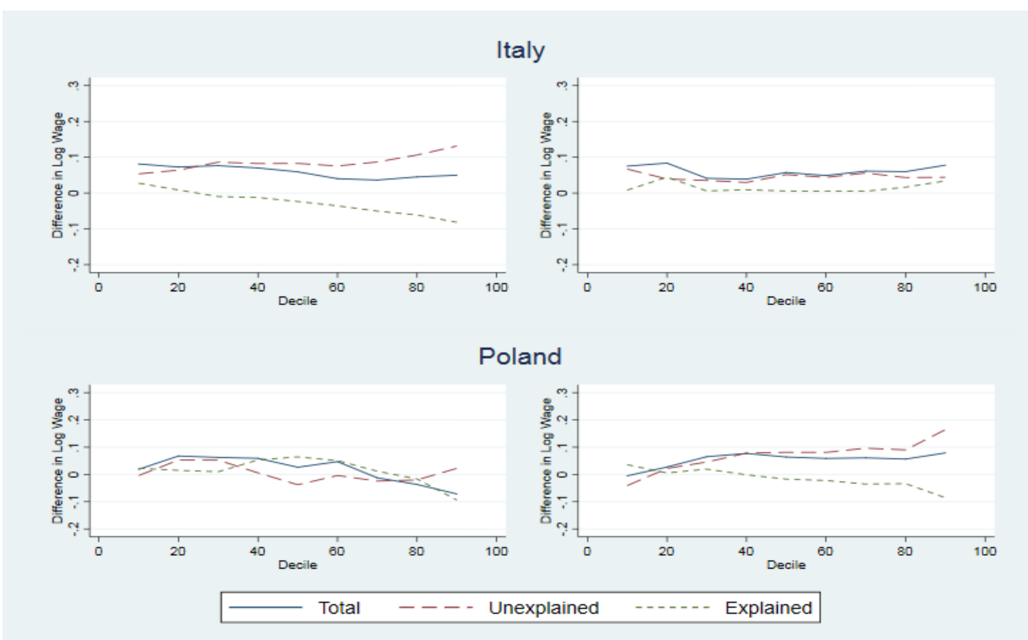
The second example for a high gender wage gap country is Portugal. Despite the gap being on average smaller than in Austria in the first period, it does not decrease over

Figure 3: Gender Gap in Gross Hourly Wages

(a) Countries with a High Gender Wage Gap



(b) Countries with a Low Gender Wage Gap



Note: Decomposition of change in gross hourly wage is performed by decile.

Source: Author's own representation based on EU-SILC and O*NET data.

time and remains above the level of Austria for the second period. However, the pattern alters between 2004 and 2016. While the difference in wage between men and women is particularly high in the left tail of the wage distribution, the gap considerably decreases in this part but rose for the high wages. Women in lower paid occupations seem to be able to reduce the difference in wages to male workers in low-paid jobs, while the reverse is apparent for high-paid jobs.

When making a Europe-wide comparison, the gender pay gap in Italy is relatively low. In 2004-2006 the gap appears as slightly decreasing along the wage distribution at a level between approximately 4 and 8 log points. Except for the bottom end of the distribution where the gender wage gap remain unchanged, the gender differences in hourly wage decrease in the middle of the distribution, leaving a U-shaped pattern for the magnitude of gender wage gaps.

Poland is another example for a low-gap country but is distinct from the others as the gender wage gap is found to rise over time. Another particularity of this country is the negative gender wage gap at the highest deciles in the earlier period. Between 2004 and 2016 the largest gender wage gaps relocate from the bottom of the wage distribution to the middle and top of the distribution.

Despite the persistence of gender discrepancies in wages, the determinants, in particular in light of the ongoing technological change, might alter over time. The different dynamics of task measures presented in Appendix Table 4 gives a first indication for digitalization and robotization being relevant determinants of a change in the driving factors of the gender wage gap. While women are employed in occupations intensive in interactive tasks, men perform more routine work. The diverging focus in skills of the occupations held by men and women may enhance gender-implications of technological change. A detailed decomposition of the gender wage gap is performed separately for countries with a high and low gap. A discussion of the results follows in section 7.

6 Decomposition Results

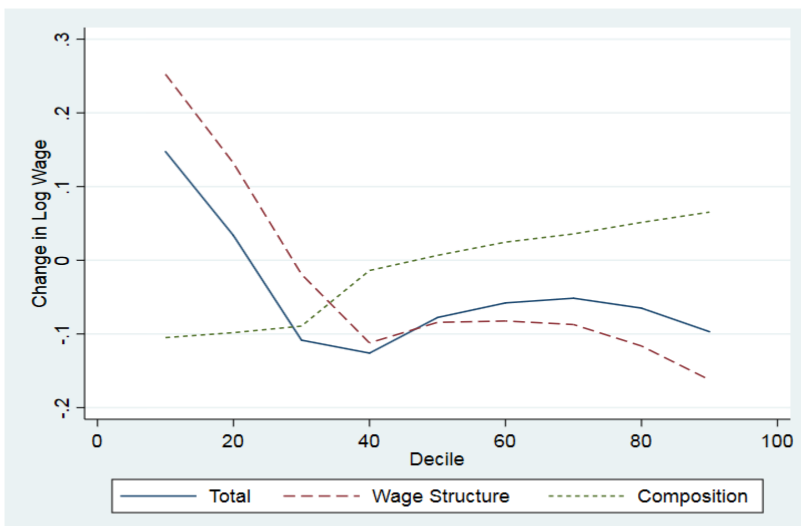
The decomposition method introduced in section 3 and specified for the empirical application in section 3.3 is now performed using the presented data. The unconditional quantile regression decomposition technique allows an evaluation of each factor's contribution to changes in the wage distribution. The considered covariates include work experience, sex, education (5 categories), contract type, part time, industry sector (10 categories) and quartile dummies for the upper three quartiles of the occupational task measures. For the purpose of a clear presentation of the results, the coefficients of the explanatory variables are summed up according to the categories defined in section 4. For the task measure, the coefficient for the highest quartile is reported. As a base group serves the modal subgroup of the weighted sample. Thus, the base group consists of male workers with a permanent, full-time job in the production and manufacturing sector and occupational task measures in the lowest quartile of the range who completed upper secondary education.

The tables showing the decomposition results are provided in the Appendix (section 9, Tables 6-11). The displayed coefficients state changes in log points if multiplied by 100. The effects have to be interpreted as the contribution of the group relative to the base group. The upper panel of Tables 9-11 provides the respective results of the aggregate decomposition of the interquartile range changes. The there presented wage structure effect corresponds to a *pure* wage structure effect ($\Delta_{S,p}$), only resulting from changes in the returns to the covariates. Similar for the composition effect: the stated *pure* composition effect ($\Delta_{X,p}$) stems only from the variation in the distribution of characteristics between the two groups considered. For reasons of completeness, the reweighting ($\Delta_{S,e}$) and specification errors ($\Delta_{X,e}$) are indicated at this point. The generally small reweighting errors imply that the estimated reweighting factors are very close to the actual reweighting function. Except for a few cases, the used specification of the linear RIF regression provides a fitting approximation of the quantile regression. The three tables show the detailed decomposition results for the contribution of each set of explanatory characteristics to the wage structure and the composition effect on the left-hand and right-hand side of the lower panel, respectively.

6.1 Wage Dynamics in the Population: Results for the Pooled Sample

A first overview is given given by Figure 4 depicting the overall wage changes across the deciles of the wage distribution. The negative slope of the graphed wage differentials signals an overall decrease in wage inequality between 2004 and 2016. This trend is mainly driven by the wage increases in the left part the distribution. The strong decline in wage growth over the first deciles flattens out for the second half of the wage distribution where wage changes are more equal for all deciles. A more pronounced change for the 50-25 than for the 75-50 log wage differential is suggested by this pattern.[12] Mainly, the observed dynamics arise from changes in wage structure which partially account for more than 100 percent of the alteration in the inequality measure. Changes in characteristics, captured by the composition effect, counteract and thus mitigate the wage structure effect.

Figure 4: Aggregate Decomposition of Change in Gross Hourly Wage (Pooled, 2004-2016)



Note: Decomposition of change in gross hourly wage is performed by decile.
Source: Author's own representation based on EU-SILC and O*NET data.

The main objective of the thesis is to identify the impact of technological progress and

[12] For a deeper understanding of inequality dynamics it would be valuable to additionally consider interquartile ranges incorporating wider ranges of the wage distribution. Due to concerns regarding the data quality at the outer ends of the wage distribution, I refrain from these indices.

workplace digitalization on workers' wages and the wage inequality indicators. This can be achieved by analyzing the so-called detailed decomposition. While the so far discussed results can be obtained simply by reweighing, the detailed decomposition results require the RIF-regression coefficient estimates in order to determine the contribution of each explanatory variable to the change in the interquartile ranges. The effect of technological change on remuneration of human labor is captured by the wage structure effects of the three technology variables (service, abstract and routine). Composition effects linked to task variables reflect within-occupation changes in technology and offshorability measures but also arise from differences in occupations held by the individuals between the years. Additionally, the estimated endowment effects are in part, despite their statistical significance, very small in magnitude which raises doubt about their economic relevance. Thus, the key focus in the further discussion of the results lies on the wage structure effect and in particular on the one related to occupational task and offshorability measures.

Overall, changes in endowment with characteristics alone would have resulted in a rise of wage inequality between 2004 and 2016. This dynamic also becomes evident in Figure 4. Composition effects are positive for the top wage deciles while the opposite can be observed for the bottom deciles. Thus, the distribution of characteristics changed to the better of the high-wage earners.

In general, there exist various determining factors for the interquartile ratios that need to be considered. The detailed composition effects for the pooled sample are reported in the lower right panel of Table 9. Education, personal as well as job characteristics-related composition effects play a substantial role in the change of the interquartile ranges due to changes in the distribution of covariates. Education accounts for 50% of the difference in the 50-25 log wage differential between 2004 and 2016 explained by workers' characteristics and for an even larger share of the explained shift in the top-end inequality. The finding suggests that workers' education improved increasingly along the wage distribution and individuals at the bottom end were unable to catch up with those at the top deciles of the wage distribution in this point.

The detailed wage structure effects are reported in the lower left panel of Table 9.

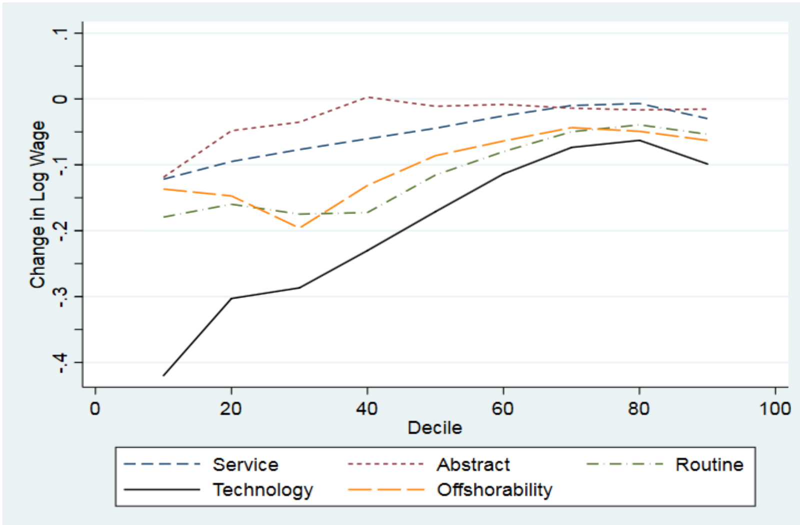
The wage structure results show that the included independent variables overexplain the reduction of the 75-25 and 50-25 interquartile ranges. Outstanding in magnitude are the coefficients capturing the impact of changes in returns to workers' characteristics described by the sets of covariates "education" and "personal characteristics". Considering changes in returns to education, the results show particular importance of this factor at the bottom part of the wage distribution. The presented effect moves in the reverse direction of the inequality dynamics. This finding, despite going opposite the total wage structure effect, is in line with results from related literature (e.g. Firpo, Fortin, and Lemieux (2011)). Contributing greatly towards the decrease in the 75-25 and 50-25 ratios is the variation in remuneration of personal characteristics. Stronger increases in returns to experience over time for low-paid occupations may be a source of the observed pattern.

The decomposition results show that the task variables capturing technological change play a substantial role as determinants of wage level and wage inequality changes. The estimated effects of the technology measures (as shown in Table 9) exhibit a dispersion-driving effect. For the 75-50 log wage differential the estimated effect of task and offshorability variables has a magnitude of roughly 16 log points. Changes in returns to occupational tasks linked to technological change increased the 50-25 gap by even 22 log points. Technological progress thus has an unbalancing effect on the wage distribution.

Before further discussing the detailed wage structure effects linked to occupational task measures for the interquartile ranges, it is informative to consider the respective effects of each of the four measures of technological change and globalization at distinct points of the wage distribution. Figure 5 shows the effects for the occupational task measures at each wage decile. Looking at the detailed decomposition suggests a changing role of each variable along the wage distribution. Figure 5 shows that technological change has the most pronounced effects in the lower half of the distribution. In the right tail, the effects appear generally more moderate and uniform. Apart from the service component which is converging towards zero up until the 8th decile, the task variables exhibit largely non-monotone effects along the wage distribution.

An interesting finding is that returns to service tasks decreased over time. The pattern

Figure 5: Detailed Decomposition of Wage Structure Effect of Task Measures (Pooled, 2004-2016)



Note: Decomposition of change in gross hourly wage is performed by decile. "Technology" sums up the coefficients of routine, service and abstract.
Source: Author's own representation based on EU-SILC and O*NET data.

of the service effect can be further interpreted as follows: Ceteris paribus, there would have been a decrease of wages that is particularly pronounced in the lower tail of the wage distribution leading to a rise of wage inequality. The decrease in returns to service tasks may be caused by supply-demand mechanisms. While some middle-skilled workers improve their education and pick up more complex tasks, others supply more service-oriented work which is then a skill over-supplied on the labor market and induces returns to service-intensive tasks to fall.

Unexpectedly, returns from abstract tasks do not rise between 2004 and 2016. The hypothesis of skill-biased technological change suggests the above-described increased demand for high-skill workers. Another plausible explanation for rising returns is the productivity-enhancing nature of digital technology for specific tasks that results in a rise of remuneration for the affected workers. However, returns to abstract tasks surprisingly do not change substantially. In total, the coefficients of the occupational task variables accumulate to an overall wage-decreasing contribution of computerization and automation.

Next, let us analyze the effects of occupational task measures indicating technological change on the inequality measures. The findings presented in Table 9 are in line with the expectations from theory explained in section 1 and 2. While returns to routine tasks play a similar role for changes in 75-50 and 50-25 gaps, the variable related to abstract tasks is highly relevant for the inequality dynamics in the bottom part of the distribution. The offshorability indicator of an occupation mainly drives left-tail dynamics signalling a more severe exposition of low-wage workers to the consequences of globalization.

As stated above, Table 9 shows the high importance of the routine component for inequality changes. This finding states that a automation-accompanying increase in the discrimination of routine-intensive tasks through remuneration increases wage dispersion as it particularly concerns low-wage earners. The effects related to the routine component are in line with the routine-biased technological change hypothesis.

The abstract component does not function as strongly wage-unequalizing as the other task measures. Shifts in the 75-50 log wage differential explicable by changing payment of abstract tasks are not significantly different from zero. Table 9 shows that this component mainly drives the dynamics through its impact on the bottom-end inequality index. Indeed, this effect can be explained by technological change as well.

Combining the last two results demonstrates the pattern of the impact of technology through digitalization and automation on wage inequality. Routine tasks proof to be important for overall wage inequality while abstract tasks' relevance for wages spreads increasingly from the top to the middle parts of the distribution.

Shifts in the 75-50 and 50-25 log wage differentials explicable by changing changing payment of service tasks are of equal sizes. This indicates an incremental discrimination of service-intensive tasks in low-skill relative to high-skill occupations over time.

Offshorability entails a smoothly increasing, wage-decreasing impact along the distribution. Returns to tasks classified as highly possible to offshore further contribute to the dispersion of wages along the distribution. This is in line with the findings for the US (see e.g. Firpo, Fortin, and Lemieux (2011)) where offshorability intensity also appears as a major determinant of the rise in inequality in the bottom-end of the wage distribution.

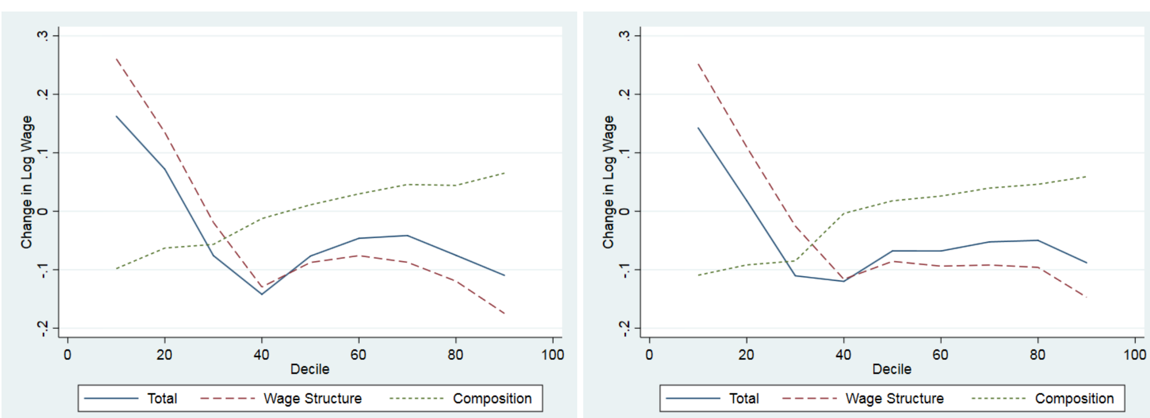
6.2 Gender-Specific Wage Changes: Women vs. Men

Even though the above analysis provides a good insight into the overall wage inequality dynamics and the role of technology in this context, the results have to be apprehended critically. Besides the significant influence of the structure of data included due to the restricted number of countries used, an additional issue to bear in mind is the difference in occupational choices between men and women. Changes in wage inequality and the corresponding impact of time-varying returns to occupational tasks can exhibit diverging patterns between the sexes. To shed light on this topic, I perform the above decomposition separately for men and women.

A comparison of the overall wage changes between the first period $(2004-2006)$ and the second period $(2014-2016)$, shown in Figures 6a and 6b depict similar patterns for men and women: a substantial increase in wage was evident for the first two deciles while the change was negative in the subsequent deciles. For both men and women, the individuals at the 4th decile experience the most pronounced decrease in wages.

Figure 6: Aggregate Decomposition of Change in Gross Hourly Wage by Gender (2004-2016)

(a) Female Sample (b) Male Sample



Note: Decomposition of change in gross hourly wage is performed by decile.
Source: Author's own representation based on EU-SILC and O*NET data.

Let us first analyze the population of females. Concerning the size of changes in the interquartile ranges, the results for females show a similar pattern compared to the decomposition results of the pooled sample. However, the inequality declines between female workers are larger in magnitude (see Table 7). Again, the wage structure effect mainly drives these variations while the composition effect is much flatter along the distribution. Table 10 provides the estimates of the detailed decomposition. Since the endowment effects, in particular of the covariates capturing differences in occupational tasks, are insignificant and close to zero, the focus lies on the interpretation of alterations in returns to the included personal and occupational characteristics.

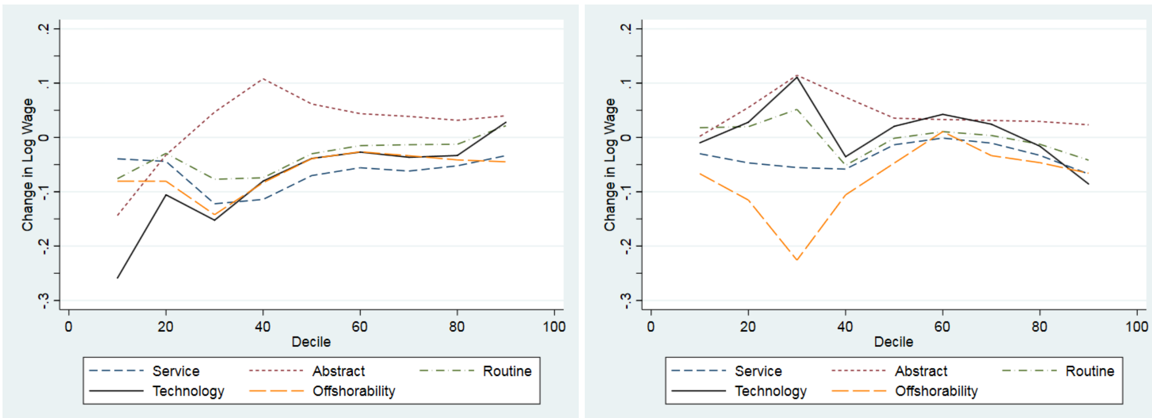
However, I briefly want to mention two sets of explanatory variables that exhibit significant composition effects and would have, ceteris paribus, led to an increase in wage inequality among females. Specifically, this concerns education as well as job characteristics (part time job and temporary contract). Women in the upper and middle part of the wage distribution experience strong increases in education while those in the left tail are subject to a phenomenon known as *"sticky floors"* in gender economics.

The direction of variation in log wage differentials at the lower tail of the distribution mainly sources in diverging returns to industry dummies and personal characteristics such as experience and marital status. Yet, there exist some counteracting forces. Technological change clearly has an overall destructive impact on the decrease of wage inequality for women. While the processes of digitalization and automation appears to have a strong inequality-enhancing effect on the 50-25 interquartile range, the opposite influence on wage inequality exists in the right tail of the distribution. Female workers in the lower two quantiles were the ones that suffered extensively from the negative consequences of technological changes between 2004 and 2016.

Figure 7 depicts the effect of the three technology measures, their sum as well as the coefficients for the offshorability variable by decile of the wage distribution separately by gender. Decomposing the inequality-driving implications of technology for women into the separate effects of each of the task measures shows that the change in returns to occupational task indices generally vanishes along the wage distribution (this particularly applies to the variable *routine*). Once more it becomes clearly evident that women between the 10th and 40th percentile experience the most pronounced impacts of the digitalization process.

Figure 7: Detailed Decomposition of Wage Structure Effect of Task Measures by Gender (2004-2016)

(a) Female Sample (b) Male Sample



Note: Decomposition of change in gross hourly wage is performed by decile. "Technology" sums up the coefficients of routine, service and abstract.
Source: Author's own representation based on EU-SILC and O*NET data.

Now, consider the decomposition results for men. The positive composition effects of education on the interquartile ranges are reinforced by the large impact of returns to education. This finding of expanding educational wage differentials is in line with the results of the decomposition literature (e.g. Acemoglu and Autor (2011)). However, the effects go in the reverse direction of the overall change since the 75-25 gap decreases by 2.3 log points.

When considering the inequality-implications of the task variables, looking at the wage dispersion indicators for the left and right tail of the wage distribution separately shows that the impacts differ notably for the 75-50 and the 50-25 ratios. Technological change appears to be neutral for wage inequality dynamics when investigating the detailed decomposition of the top-end wage inequality. On the other hand, the effects of technological change on wage structure explain almost the entire fall in wage divergence between the first quartile and the median.

Inferring from the information given by Figure 7b, the enhanced usage of computers and robots exhibits a varying impact on wages. While returns to abstract tasks increase in the first deciles (e.g. by above 10 log points at the 3rd decile), they grow more uniformly over time for the highest deciles at a rate of approximately 3 log points. The impact of routine and service tasks diverges in the first half of the wage distribution (remuneration of service(routine)-intensive tasks act wage-decreasing(increasing)) while showing a similar pattern with small effects in the second half. The results shown in Table 11 demonstrate that offshorability indicators are of greater importance for wage inequality between men in the labor market than technological change is. The wage structure effect linked to offshorability is negative and particularly pronounced for lower wage levels. This is also reflected in the results presented in Table 11 stating that changing returns to tasks that require no face-to-face contact or no on-site presence of the worker especially influence the wage dynamics through the inequality-driving impact on the 50-25 gap.

The above discussed results show some similarities in the determinants of wage between men and women but as much point out the presence of some non-negligible differences in wage inequality dynamics and its determinants between the sexes.

Improvements in education (captured by the endowment effect for education) is not a female phenomenon and an even stronger determinant of wage inequality for the male population. Another common feature in the estimation results concerns the size and pattern of the wage structure effect of the indicator of highly abstract tasks along the wage distribution. This effect can be directly explained by technological change. Before digitalization changed workplaces and the skill requirements for workers, abstract tasks were mainly present in the very right tail of the wage distribution. As automation progresses and spreads, occupations previously intense in routine tasks in the other parts of the distribution needed to change focus as skill demand shifted to abstract tasks. Thus, the returns to highly abstract tasks increased over time for the workers located in the middle of the wage distribution as a channel of incentives set by employers.

A striking difference though is present in the changes in returns to the other occupational task measures linked to technological change as well as its cumulated effect. While for the male population the change in occupational task-related wage structure does not play a major role for the explanation of the variation in top-end inequality between 2004 and 2016 the contrary is true for women. When looking at the separate indicators of technological change in detail, the respective significance, magnitude and sign differ across sexes and location in the wage distribution. The differences in the aggregated effect are particularly striking. Captured by the line labeled "technology", a continuously negative impact is found for the sample of women. Contrarily, the effect of technological progress is positive for the majority of deciles in the male population group. The complexity of the estimation results emphasizes the heterogeneous effects of digitalization and automation. Some implications and conclusions from the presented findings will be discussed in the last section.

7 Decomposition of the Gender Wage Gap

The findings presented in chapter 5 demonstrate that gender-differences in hourly wage are still present in 2016, however, at a changed level. Further, gender-divergences in hourly wage vary depending on the country are evident in Figure 3. Are there also differences in the vulnerability to technological change? Do gender-implications of the changing work environment exist? In order to find answers to these questions, I analyze the gender wage gaps in more detail. The new insights through the detailed decomposition results provide a base for policy decisions that aim at closing the gender wage gap.

The decomposition analysis is performed at the example of two countries. Austria is taken as an example for an economy with a high gender wage gap. On the other hand, Italy serves as a representative case for countries with an already small difference in hourly wages between men and women in 2004. The detailed findings for the three quartiles of the wage distribution are presented in Table 12-17 in the Appendix.

7.1 Austria

Austria has a comparatively high gender wage gap, that decreases from 21.9 to 17.1 log points in the median. While a fraction of 11-21% of the wage gap between men and women is explained by differences in characteristics in the earlier years, this share more than doubled for the 2nd and 3rd quartile.

Not only the size of the aggregate composition effect but also of the relevant factors driving the respective endowment effect alter between the periods. Discrepancies in personal characteristics of the workers like experience and marital status are important drivers of gender-induced wage inequalities at both points in time. Also, differences in the industry sector of employment, despite not being statistically significant, play a role in both periods. On the other hand, job characteristics determine the aggregate endowment effect of change in interquartile ranges considerably in the earlier period, while this is not the case in the later years. Disparities in education levels between men and women, that are traditionally an important factor of the explained divergence of hourly wage, do not cause wage gaps in Austria. This indicates overall equal education levels for both genders.

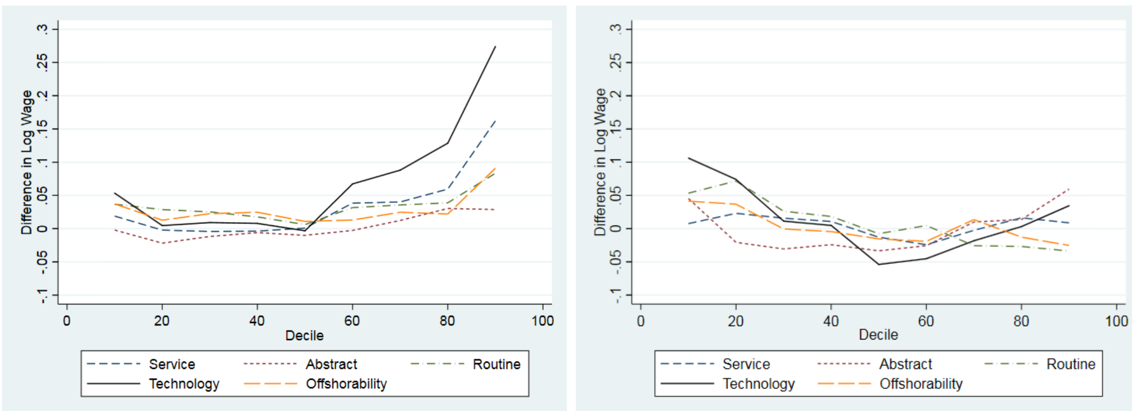
The applied decomposition method further allows for a measurement of the impact of differences in the remuneration of tasks between male and female workers. Thus, the discrimination of women through a diverging reward of alike characteristics can be quantified. The magnitude of the estimated effects for the occupational task measures emphasizes their role for the gender wage gap in Austria. Following the line of interpretation of the used framework, their altering importance for the gender wage gap results from the process of digitalization and automation.

Figure 9 illustrates again the influence of the technology proxies on the gender wage gap along the wage distribution separately for the earlier $(2004-2006)$ and later $(2014-2016)$ period. The observed change in the pattern as well as in the size of the effect over time can be attributed to technological change. While the cumulated effect of the technology measures is especially driving the divergence of wages in $2004-2006$ in the higher deciles, it exhibits a U-shaped pattern in the later period. In $2014-2016$ it contributes positively to the wage gap for the outer deciles but functions wage-equalizing in the middle of the wage distribution.

Tables 13 and 14 present the detailed coefficients of the performed decomposition respectively for each period. Diverging returns to routine tasks contributed to the dispersion

Figure 8: Detailed Decomposition of Wage Structure Effect of Task Measures for the Gender Wage Gap (Austria)

(a) 2004-2006 (b) 2014-2016



Note: Decomposition of change in gross hourly wage is performed by decile. “Technology” sums up the coefficients of routine, service and abstract.
Source: Author’s own representation based on EU-SILC and O*NET data.

of wage between the genders in $2004-2006$. The explanatory power of the wage structure effect linked to this variable is especially pronounced in the tails. Returns to factors like education, however, contribute to a closing of the gender wage gap. Surprisingly, returns to abstract tasks also equalize the pay for men and women in the lower two quartiles of the wage distribution. This is an instance for positive discrimination of women.

In the later years, structural discrimination affecting women at the 25th decile mainly takes place through the channel of remuneration of routine- and service-intensive tasks while in the right tail of the wage distribution diverging returns to highly abstract tasks are determining the gender-based wage differences. Considering the role of remuneration of abstract tasks in the years $2014-2016$, a notable change of magnitude can be observed compared to the earlier period. The wage advantage of men decreases at all parts of the wage distribution. This can be directly linked to the often observed increase in demand for abstract skills that is accompanied by a rise in returns to abstract tasks.

7.2 Italy

Compared to Austria, the level of the gender wage gap in Italy is small. However, gender-based differences in hourly wage are evident in 2004-2006 as much as in 2014-2016. The average magnitude of the gap does not decrease considerably over this period as it is the case in other European countries. Contrary, the divergence in wage even increases for the upper deciles, e.g. by 0.67 log points at the 3rd quartile, and remains stable in the median. A decrease in wage inequality between the genders can only be observed in the left tail of the wage distribution. Hence, the pattern of the gap along the wage distribution changes over the years. While in the earlier period the size of difference in wages between men and women decreases slightly along the distribution, the gender-divergence in wages is found to be U-shaped to some degree in the later period. The latter form implies particularly distinct gender-differentials at the top and bottom of the distribution.

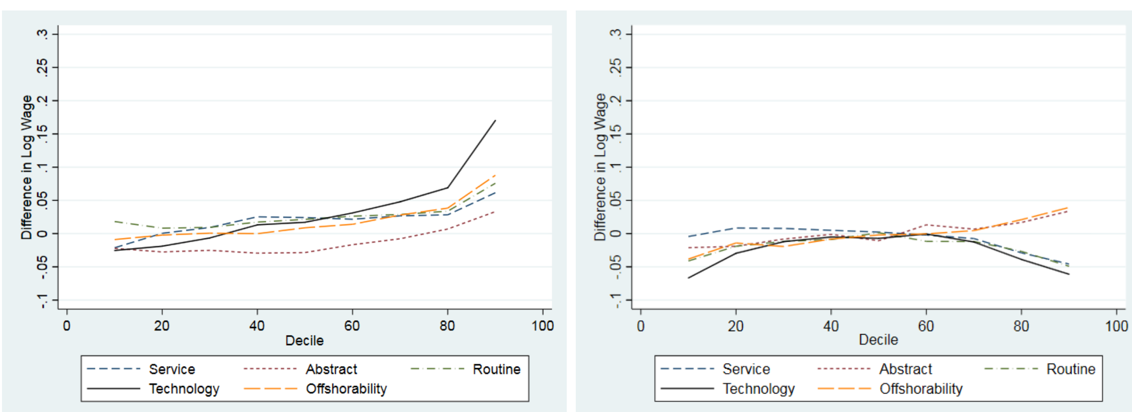
As in the case of Austria, the explained share of the wage divergence between the genders varies over time. The decomposition results for the first period indicate a negative gap caused by differences in the distribution of characteristics. Thus, if there would be the same wage structure for men and women, female workers would earn higher hourly wages than their male counterparts in the Italian labor force. Differences in the observable characteristics between the genders do not significantly alter the gap for the sample of $2014-2016$. Again, wage structure appears to be clearly discriminatory towards women. It is the main driver of the gender gap at all quartiles considered.

However, one endowment feature worth mentioning is the change in the composition effect linked to abstract tasks. The positive and significant effect detected in the later period shows that men hold more jobs that are highly intense in abstract tasks in Italy at that time. The task composition for Italy stands in opposition to the country-average in the pooled sample. The descriptive statistics of task intensity by gender presented in 4 show a higher endowment of abstract tasks in the years $2004-2006$ for female workers. However, this divergence shifts over time. In $2014-2016$ there exist no more considerable difference between abstract-intensity of jobs held by men and women.

For none of the task measures, except *abstract*, an advantageous effect for women is present in the earlier period. Discrimination through diverging returns to occupational tasks appears to enhance the wage gaps. In the beginning of the 2000s, discrimination affecting women through diverging task prices becomes more important when moving towards the right tail of the wage distribution. The explanatory power of wage structure linked to service- and routine-intensive tasks for the gender-difference play a crucial role. Of particular importance for the gender wage gap in the sample pooled for $2004 - 2006$ are, however, the abstract-intensive tasks. In this case the discriminatory wage structure present for this variable contributed significantly to the persisting wage gap along the entire wage distribution. The explanatory power of the technology proxies becomes insignificantly different from zero for the $2014 - 2016$.

Figure 9: Detailed Decomposition of Wage Structure Effect of Task Measures for the Gender Wage Gap (Italy)

(a) 2004-2006 (b) 2014-2016



Note: Decomposition of change in gross hourly wage is performed by decile. “Technology” sums up the coefficients of routine, service and abstract.
Source: Author’s own representation based on EU-SILC and O*NET data.

Comparing the two countries, I can point out similarities as much as differences in the pattern of the gender wage gap, its determining factors as well as its change. In both countries task-linked discrimination explains a smaller part of the wage inequality between men and women in the later period. In particular in the top end of the wage distribution technology measures become less important for explaining the gender gap in hourly wages.

On the other hand, the development of returns to abstract tasks between the periods exhibits a completely distinct structure in Austria and Italy. Digitalization functions wage gap-decreasing with respect to diverging remuneration of abstract tasks in Austria over time. The contrary applies to Italy where the positive discrimination through higher returns to abstract tasks of women is mitigated in $2014 - 2016$.

As the used approach allows an interpretation of changes in returns to the technology proxies to be attributable to technological progress, I can find differential consequences of digitalization and automation on the gender wage gap between the countries and, within a country, along the wage distribution. Interestingly, in Austria, the discrimination through gender-differences in returns to occupational tasks shifted from the top to the bottom of the wage distribution. Changes in wage structure linked to service tasks acted as the main channel for this alteration. In Italy, the divergence of remuneration of occupational tasks between men and women alleviate over time. In particular in the right tail of the distribution the pattern transformed from gap-enhancing in $2004 - 2006$ to neutral or even difference-diminishing. Here, the prior negative discrimination is converted to a positive discrimination of women in the labor market.

8 Conclusion

In this thesis I analyze the impact of technological change on hourly wage and wage inequality for several European Union countries in recent years. A particular focus lies on the investigation of the diverging implications for men and women. To determine the exact effects of digitalization at the workplace on hourly wage, I apply a counterfactual decomposition method proposed by Fortin, Firpo, and Lemieux (2011). A combination of sample reweighting and recentered influence function regressions allows for the finding of unbiased effects. Within this framework, technological progress is captured by the task measures which define an occupation with respect to the tasks it consists of. The used approach requires an explanation of any change in the coefficients of the technology proxies to be attributed to digitalization or automation-induced transformations of the work environment.

The methods are empirically applied to the EU-SILC dataset from 2004 to 2016. The various determinants of the change in wage inequality are defined for the variation of the 75-25, 75-50 and 50-25 interquartile ranges over that period. Additionally, the gender wage gap in the samples pooled for the years $2004-2006$ and $2014-2016$ is decomposed into its driving factors.

Independent of the measure, wage inequality tends to decrease over time. However, the driving forces are found to diverge across several dimensions. Considering the overall wage gaps, the dynamics are mainly caused by the decline in the 50-25 ratio. Among other factors like a cutback in the discrimination of low-wage earners with regard to their personal characteristics, technological change plays an important role. The differences in the impact of digitalization and automation along the wage distribution shape the inequality dynamics.

An interesting insight to the structure of the effect is given by the separate analysis of the data for the male and female population groups. While some similarities can be detected in the detailed analysis, the overall implications of the digitalization process diverge between the genders. The outstanding rise in returns to the abstract task variable may reflect the increased demand for high-skilled cognitive tasks following technological progress. The coefficient of the abstract tasks indicator shows a similar pattern in both the females' as well as males' wage distribution. Other findings let me conclude that technological change has different implications for male and female workers. Women at lower quantiles of the distribution suffer particularly from the fall in remuneration of routine tasks as a consequence of technological change. On the contrary, factors related to the spread of digital technology did not appear to have this significant inequality-increasing impact on the 50-25 ratio in the sample of men.

Further evidence is provided by the decomposition results for the gender wage gap. The differences in the respectively estimated coefficients between the periods emphasize the shift in determinants of gender-based wage differentials over time. These transformations can be partly attributed to technological change. In both countries considered, the discrimination of females through returns to routine tasks becomes less important for explaining the gender wage gap along the entire wage distribution. This may be related to the general decrease in the importance of routine tasks as a consequence of substitution of human labor in computerizable jobs. Interestingly, in Austria, the discrimination through gender-differences in returns to occupational tasks shifts from the top to the bottom of the wage distribution. Similarly in Italy the gap-widening effect of the technology proxies in the right tail disappear over time. This outcome emphasizes once again the variation of implications of technological change along the wage distribution.

The heterogeneity of the results confirms the necessity of an approach that allows for a precise analysis of the effects. The applied methodology meets these requirements as it enables a decomposition along different dimensions.

Generally speaking, the empirical findings are in line with the results presented in related literature. For the US, Firpo, Fortin, and Lemieux (2011) show that technological change impacts male and female workers through different channels. Naticchioni, Ragusa, and Massari (2014) find that the importance of technology-related task measures for hourly wage varies along the wage distribution and thus contributes significantly to changes in wage inequality.

However, the results should be interpreted with caution. Due to data limitations the dynamics in the considered countries shape the estimated effects. Performing the analysis for a larger set of countries and only pooling countries which exhibit similar patterns of wage inequality changes would be valuable to draw further conclusions. Distinguishing only between 22 occupational groups implies the problematic assumption of no differences in tasks within one of these broadly defined professional categories. Thus, further improvement with regard to the used data would be provided by a more disaggregated classification of occupations.

Especially given the findings of gender-differences in the impact of technology on wage and wage inequality, research should be pursued in this direction. My thesis provides thorough evidence for the divergent implications of technological change for different income groups. The gained insights contribute to an understanding of the determinants of wage differentials between male and female workers necessary for further steps towards equalizing policy making. However, for targeted actions, a knowledge of more specific structures is necessary. Thus, a closer analysis of certain particularly affected occupation groups is desirable. For this purpose I suggest to study the effects on wages as well as income using the above applied approach complemented by a more detailed investigation of within-occupation changes, like e.g. Spitz-Oener (2006) perform, based on microdata for a specific country.

So far, I only consider overall wage inequality as well as gender-related divergences. Another aspect that may proof interesting to be analyzed in the context of digitalization is its impact on wages with respect to different age groups. Clearly, the method used in this thesis can be applied to various questions of similar type. The results provide helpful information regarding the determinants of wage and the driving forces of wage inequality.

9 Appendix

9.1 Tables: Descriptive Statistics

Table 1: Sample Means

	2004-2006		2014-2016	
	Women	Men	Women	Men
Mean Wage	9.45	10.51	8.76	9.84
Log Wage	1.98	2.10	1.96	2.07
Married	0.626	0.657	0.610	0.630
Experience (in Yrs.)	16.47	18.33	19.28	20.80
Primary Education	0.096	0.120	0.048	0.058
Lower Secondary Education	0.169	0.248	0.124	0.190
Secondary Education	0.424	0.437	0.438	0.494
Post-Secondary Education	0.083	0.047	0.044	0.024
Tertiary Education	0.228	0.148	0.347	0.233
Permanent Contract	0.877	0.887	0.844	0.853
Part Time Job	0.203	0.039	0.157	0.031
Occupations				
Managers	0.023	0.035	0.029	0.040
Science,Engineering,IT Professionals	0.008	0.026	0.021	0.052
Health Professionals	0.030	0.013	0.033	0.011
Teaching Professionals	0.124	0.031	0.110	0.031
Business,Legal,Cultural Professionals	0.042	0.028	0.071	0.042
cience,Engineering,IT Associate Professionals	0.017	0.074	0.017	0.072
Health Associate Professionals	0.041	0.011	0.047	0.016
Other Associate Professionals	0.120	0.071	0.097	0.067
Office Clerks	0.138	0.087	0.130	0.076
Customer Service Clerks	0.054	0.023	0.031	0.015
Service, Personal Care, Security Workers	0.101	0.065	0.102	0.064
Sales Workers	0.070	0.023	0.103	0.037
Skilled Agricultural & Fishery Workers	0.004	0.013	0.003	0.012
Building Workers	0.005	0.099	0.002	0.077
Metal & Machinery Workers	0.008	0.107	0.005	0.120
Precision, Handicraft & Printing Workers	0.009	0.012	0.005	0.011
Food Processing, Wood & Other Workers	0.044	0.047	0.036	0.037
Stationary Plant Machine Operators & Assemblers	0.042	0.081	0.033	0.062
Drivers & Mobile Plant Operators	0.004	0.075	0.003	0.077
Elementary Sales & Service Laborers	0.097	0.040	0.100	0.038
Agricultural & Fishery Laborers	0.005	0.007	0.004	0.011
Mining, Manufacturing & Transporting Laborers	0.014	0.033	0.018	0.030

Table 1 – continued

	2004-2006		2014-2016	
	Women	Men	Women	Men
Sectors				
Manfacturing & Production	0.207	0.367	0.165	0.358
Construction	0.013	0.117	0.011	0.109
Wholesale & Retail	0.133	0.102	0.145	0.118
Transport	0.031	0.082	0.024	0.080
Hotels & Accomodation	0.037	0.019	0.045	0.027
Services, R&D, IT	0.104	0.083	0.153	0.123
Public Administration	0.082	0.090	0.078	0.075
Education	0.163	0.042	0.152	0.042
Health	0.135	0.040	0.147	0.037
Other Services	0.091	0.055	0.077	0.025
Observations	37597	46214	44387	46348

Note: Sample means computed using sample weights.

Source: Authors' calculations based on EU-SILC data.

Table 2: Mean Wage by Occupation (in 2015 EUR)

		2004-2006		2014-2016	
		Women	Men	Women	Men
	Highest Paid Occupations				
23	Teaching Professionals	15.22	17.5	11.85	14.19
32	Health Associate Professionals	12.36	12.83	11.34	12.23
22	Health Professionals	9.85	20.46	9.46	17.68
10	Managers	10.11	15.57	9.85	13.71
21	Science,Engineering,IT Professionals	10.73	12.57	11.24	12.94
42	Customer Service Clerks	10.65	14.84	8.97	11.9
24	Business,Legal,Cultural Professionals	9.86	13.39	9.64	12.7
	Middle Paid Occupations				
31	Science,Engineering,IT Associate Professionals	9.18	13.16	9.51	12.19
34	Other Associate Professionals	9.85	12.58	9.61	12.09
41	Office Clerks	9.79	11.34	9.9	10.14
51	Service, Personal Care, Security Workers	7.87	10.5	7.31	8.73
81	Stationary Plant Machine Operators & Assemblers	7.5	9.37	6.35	7.95
73	Precision, Handicraft & Printing Workers	7.67	9.24	7.93	9.41
72	Metal & Machinery Workers	8.41	8.35	6.98	8.6
71	Building Workers	8.67	7.58	5.85	7.49
83	Drivers & Mobile Plant Operators	7.19	8.23	5.96	7.3
61	Skilled Agricultural & Fishery Workers	6.88	7.97	5.69	7.08
91	Elementary Sales & Service Laborers	6.57	8.55	6.52	8.28
	Lowest Paid Occupations				
93	Mining, Manufacturing & Transporting Laborers	6.16	7.87	5.23	7.48
92	Agricultural & Fishery Laborers	6.43	6.91	6.17	6.77
52	Sales Workers	6.28	7.85	6.66	8.53
74	Food Processing, Wood & Other Workers	5.07	8.00	5.98	6.94

Notes: Ranking according to mean hourly wage in earlier period. Mean hourly wage of an occupational group computed using sample weights.
Source: Authors' calculations based on EU-SILC data.

Table 3: Task Measure By Occupation

	2004-2006				2014-2016			
	S	A	R	O	S	A	R	O
Managers	3.36	3.35	1.98	2.25	3.53	3.41	1.82	2.05
Science& IT P.	2.74	3.38	1.97	2.51	2.92	3.34	1.87	2.37
Health P.	3.51	3.33	2.29	1.94	3.75	3.29	2.08	1.77
Teaching P.	3.42	3.13	1.74	2.26	3.40	3.16	1.65	2.13
Business & Legal P.	3.16	3.04	1.68	2.59	3.33	3.14	1.58	2.38
Science & IT AP	2.55	2.97	2.53	2.23	2.83	3.12	2.51	1.86
Health AP	3.40	3.08	2.27	2.00	3.52	3.07	2.36	1.64
Other AP	3.25	3.00	1.81	2.45	3.29	3.00	1.84	2.20
Office C.	2.75	2.67	1.87	2.63	2.97	2.77	1.76	2.37
Customer Service C.	3.52	2.79	1.88	2.26	3.44	2.8	1.60	2.25
Service, Care, Sec. W.	3.37	2.71	2.25	2.07	3.42	2.85	2.26	1.82
Sales W.	3.18	2.17	1.66	2.63	3.37	2.65	1.84	2.20
Agriculture W.	2.03	2.33	2.78	2.35	2.77	2.79	2.79	1.80
Building W.	2.15	2.49	2.72	2.31	2.82	2.80	2.8	1.68
Metal & Machinery W.	1.99	2.48	3.01	2.20	2.71	2.85	2.89	1.67
Handicraft W.	1.68	2.12	2.57	2.68	2.73	2.7	2.65	1.98
Food & Wood W.	1.73	2.20	2.69	2.71	2.64	2.62	2.66	1.95
Stat. Plant W.	1.66	2.22	2.94	2.46	2.48	2.64	2.86	1.83
Drivers & Mob. Plant W.	2.32	2.43	2.84	2.03	2.94	2.81	2.71	1.63
Sales & Service L.	2.70	2.33	2.20	2.31	2.86	2.46	2.48	1.92
Agriculture L.	1.65	2.01	2.92	2.55	2.80	2.62	2.79	2.76
Mine & Manuf. L.	2.09	2.15	2.62	2.22	2.77	2.64	2.74	1.67

Note: P=Professional; AP= Associate Professional; C=Clerks; W=Worker; L=Laborer; S=Service; A=Abstract; R=Routine; O=Offshorability

Source: Authors' calculations based on O*NET data.

Table 4: Occupational Task Measure By Gender

	Men		Women	
	2004-2006	2014-2016	2004-2006	2014-2016
Service	2.53	2.99	2.97	3.19
Abstract	2.61	2.89	2.73	2.88
Routine	2.41	2.34	2.06	2.03
Offshorability	2.34	1.94	2.37	2.07

Note: Mean task measure by gender computed using sample weights.

Source: Authors' calculations based on O*NET and EU-SILC data.

Table 5: Gross Hourly Wage By Country (in 2015 EUR)

		1st Quartile		Median		3rd Quartile		Mean	
		2004-06	2014-16	2004-06	2014-16	2004-06	2014-16	2004-06	2014-16
AT	Pooled	10.05	10.67	13.08	13.96	17.08	18.52	14.61	15.57
	Women	8.97	9.89	11.45	12.68	15.26	17.06	12.96	14.10
	Men	11.40	11.63	14.62	15.04	18.38	20.00	15.91	16.85
IT	Pooled	7.24	7.20	11.35	11.27	14.85	14.11	12.82	12.06
	Women	8.63	8.66	10.97	10.96	14.61	13.85	12.42	11.63
	Men	9.33	9.24	11.62	11.54	15.01	14.42	13.11	12.42
PL	Pooled	1.85	2.59	2.65	3.55	4.06	5.19	3.38	4.33
	Women	1.77	2.56	2.65	3.45	4.13	4.96	3.38	4.18
	Men	1.91	2.73	2.70	3.69	4.04	5.39	3.38	4.48
PT	Pooled	3.23	3.71	4.25	5.07	6.85	8.27	6.08	6.84
	Women	2.91	3.43	3.92	4.55	6.63	7.69	5.89	6.29
	Men	3.47	4.07	4.58	5.58	6.92	8.74	6.25	7.42

Note: Mean gross hourly wage by gender computed using sample weights.

Source: Authors' calculations based on EU-SILC data.

9.2 Tables: Decomposition Results

Table 6: Aggregate Decomposition of Change in Gross Hourly Wage Inequality (Pooled Sample, 2004-2016)

Interquartile Range	q_{75-25}	q_{75-50}	q_{50-25}
Overall Change (Δ_O)	-0.0271**	0.0171***	-0.0442***
	(0.00932)	(0.00432)	(0.00849)
Composition Effect (Δ_X)	0.144***	0.0373***	0.107***
	(0.0104)	(0.00448)	(0.0100)
Wage Structure Effect (Δ_S)	-0.166***	-0.0183***	-0.147***
	(0.0104)	(0.00424)	(0.00870)
Observations	174546	174546	174546

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 7: Aggregate Decomposition of Change in Gross Hourly Wage Inequality (Women, 2004-2016)

Interquartile Range	q_{75-25}	q_{75-50}	q_{50-25}
Overall Change (Δ_O)	-0.0641***	0.0159*	-0.0800***
	(0.0122)	(0.00675)	(0.0110)
Composition Effect (Δ_X)	0.112***	0.0402***	0.0717***
	(0.0165)	(0.00706)	(0.0164)
Wage Structure Effect (Δ_S)	-0.176***	-0.0243**	-0.152***
	(0.0178)	(0.00745)	(0.0165)
Observations	81984	81984	81984

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 8: Aggregate Decomposition of Change in Gross Hourly Wage Inequality (Men, 2004-2016)

Interquartile Range	q_{75-25}	q_{75-50}	q_{50-25}
Overall Change (Δ_O)	-0.0231	0.00525	-0.0283**
	(0.0126)	(0.00537)	(0.0109)
Composition Effect (Δ_X)	0.127***	0.0152**	0.112***
	(0.0148)	(0.00585)	(0.0128)
Wage Structure Effect (Δ_S)	-0.150***	-0.00997	-0.140***
	(0.0144)	(0.00638)	(0.0132)
Observations	92562	92562	92562

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 9: Detailed Decomposition of Change in Gross Hourly Wage (Pooled Sample, 2004-2016)

Interquartile Range	q_{75-25}	q_{75-50}	q_{50-25}	q_{75-25}	q_{75-50}	q_{50-25}
Aggregate	*Wage Structure Effect*			*Composition Effect*		
Pure Effect	-0.166***	-0.0183***	-0.147***	0.143***	0.0391***	0.104***
	(0.0104)	(0.00424)	(0.00870)	(0.00842)	(0.00262)	(0.00757)
Error	-0.00861	-0.00384*	-0.00477	0.00139	-0.00182	0.00321
	(0.00696)	(0.00166)	(0.00612)	(0.00962)	(0.00419)	(0.00920)
Detailed	*Pure Wage Structure Effect*			*Pure Composition Effect*		
Service	0.0925***	0.0425***	0.0500***	-0.00462***	-0.00109*	-0.00352***
	(0.0166)	(0.00696)	(0.0148)	(0.00128)	(0.000471)	(0.00104)
Abstract	0.0283**	-0.000653	0.0290***	-0.0160***	0.00204**	-0.0180***
	(0.0107)	(0.00644)	(0.00848)	(0.00208)	(0.000766)	(0.00201)
Routine	0.134***	0.0732***	0.0603***	-0.00104	-0.000257	-0.000787
	(0.0169)	(0.00801)	(0.0160)	(0.00125)	(0.000489)	(0.00108)
Offshoring	0.130***	0.0439***	0.0856***	0.0146***	0.00352***	0.0110***
	(0.0128)	(0.00647)	(0.0122)	(0.00194)	(0.000596)	(0.00153)
Education	0.201***	0.00931	0.191***	0.0713***	0.0201***	0.0512***
	(0.0119)	(0.00607)	(0.0102)	(0.00492)	(0.00172)	(0.00431)
Sector	-0.00483	0.00127	-0.00610	0.00552*	0.00310***	0.00242
	(0.0171)	(0.00859)	(0.0166)	(0.00215)	(0.000700)	(0.00193)
Personal Char.	-0.176***	0.00253	-0.178***	0.0364***	0.00883***	0.0276***
	(0.0259)	(0.0128)	(0.0221)	(0.00259)	(0.000984)	(0.00222)
Job Char.	0.117***	-0.134***	0.251***	0.0343***	0.00498***	0.0293***
	(0.0300)	(0.0113)	(0.0272)	(0.00216)	(0.000556)	(0.00191)
Constant	-1.074***	-0.235***	-0.839***	-	-	-
	(0.0989)	(0.0431)	(0.0952)			
Observations	174546	174546	174546	167622	167622	167622

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 10: Detailed Decomposition of Change in Gross Hourly Wage Inequality (Women, 2004-2016)

Interquartile Range	q_{75-25}	q_{75-50}	q_{50-25}	q_{75-25}	q_{75-50}	q_{50-25}
Aggregate	*Wage Structure Effect*			*Composition Effect*		
Pure Effect	-0.167***	-0.0204**	-0.147***	0.121***	0.0373***	0.0841***
	(0.0155)	(0.00746)	(0.0142)	(0.0126)	(0.00387)	(0.0115)
Error	-0.00861	-0.00384*	-0.00477	-0.00946	0.00290	-0.0124
	(0.00696)	(0.00166)	(0.00612)	(0.0130)	(0.00666)	(0.0138)
Detailed	*Pure Wage Structure Effect*			*Pure Composition Effect*		
Service	0.0210	0.0124	0.00867	-0.000873	-0.000391	-0.000482
	(0.0169)	(0.0100)	(0.0145)	(0.000946)	(0.000444)	(0.000836)
Abstract	0.0205	-0.0287***	0.0492**	0.00312	-0.000301	0.00342
	(0.0196)	(0.00851)	(0.0165)	(0.00237)	(0.000307)	(0.00260)
Routine	0.0372	0.0175	0.0196	-0.0000429	-0.000382	0.000339
	(0.0210)	(0.0124)	(0.0185)	(0.000440)	(0.000362)	(0.000383)
Offshoring	0.0717***	0.00635	0.0653***	0.00118	0.000393	0.000786
	(0.0191)	(0.00977)	(0.0184)	(0.00147)	(0.000473)	(0.00103)
Education	0.160***	0.0257**	0.134***	0.0467***	0.0194***	0.0273***
	(0.0172)	(0.00994)	(0.0152)	(0.00781)	(0.00257)	(0.00695)
Sector	-0.0404	-0.00686	-0.0336	0.0103***	0.00252*	0.00774**
	(0.0353)	(0.0200)	(0.0318)	(0.00293)	(0.00112)	(0.00272)
Personal Char.	-0.298***	-0.0319*	-0.266***	0.0235***	0.01000***	0.0135**
	(0.0326)	(0.0158)	(0.0296)	(0.00486)	(0.00185)	(0.00425)
Job Char.	0.0994*	-0.192***	0.291***	0.0437***	0.00508***	0.0387***
	(0.0503)	(0.0180)	(0.0433)	(0.00392)	(0.00109)	(0.00337)
Constant	-0.394**	0.156*	-0.550***	-	-	-
	(0.148)	(0.0674)	(0.134)			
Observations	81984	81984	81984	75194	75194	75194

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 11: Detailed Decomposition of Change in Gross Hourly Wage Inequality (Men, 2004-2016)

Interquartile Range	q_{75-25}	q_{75-50}	q_{50-25}	q_{75-25}	q_{75-50}	q_{50-25}
Aggregate	*Wage Structure Effect*			*Composition Effect*		
Pure Effect	-0.128***	-0.00771	-0.120***	0.152***	0.0297***	0.122***
	(0.0134)	(0.00616)	(0.0124)	(0.00975)	(0.00328)	(0.00849)
Error	-0.0693***	-0.0249**	-0.0443**	-0.0250	-0.0145*	-0.0105
	(0.0204)	(0.00809)	(0.0146)	(0.0140)	(0.00574)	(0.0125)
Detailed	*Pure Wage Structure Effect*			*Pure Composition Effect*		
Service	0.0408	-0.00677	0.0475*	0.000724	-0.000706	0.00143
	(0.0245)	(0.0113)	(0.0216)	(0.000919)	(0.000429)	(0.000964)
Abstract	-0.0438**	0.000487	-0.0443**	-0.000210	-0.00113*	0.000922
	(0.0158)	(0.00691)	(0.0137)	(0.000695)	(0.000440)	(0.000693)
Routine	-0.0302	-0.00319	-0.0270	0.00396**	0.00104*	0.00291**
	(0.0268)	(0.0122)	(0.0236)	(0.00127)	(0.000447)	(0.00104)
Offshoring	0.129***	0.0125	0.116***	0.00937***	0.000861*	0.00851***
	(0.0203)	(0.00954)	(0.0166)	(0.00218)	(0.000401)	(0.00202)
Education	0.179***	-0.00254	0.182***	0.0951***	0.0180***	0.0771***
	(0.0155)	(0.00704)	(0.0141)	(0.00624)	(0.00178)	(0.00555)
Sector	-0.0709***	-0.00993	-0.0609**	0.0101***	0.00526***	0.00485*
	(0.0209)	(0.0101)	(0.0199)	(0.00276)	(0.00112)	(0.00239)
Personal Char.	-0.149***	0.0204	-0.170***	0.00339	0.00130	0.00209
	(0.0286)	(0.0120)	(0.0254)	(0.00376)	(0.00127)	(0.00328)
Job Char.	0.211***	-0.103***	0.314***	0.0375***	0.00549***	0.0320***
	(0.0430)	(0.0132)	(0.0404)	(0.00291)	(0.000760)	(0.00253)
Constant	-0.502**	0.108	-0.610***	-	-	-
	(0.154)	(0.0708)	(0.127)			
Observations	92562	92562	92562	92428	92428	92428

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 12: Aggregate Decomposition of the Gender Gap in Gross Hourly Wage (Austria)

	2004-2006			*2014-2016*		
Quartile	q_{75}	q_{50}	q_{25}	q_{75}	q_{50}	q_{25}
Overall Change (Δ_O)	0.187***	0.219***	0.243***	0.160***	0.171***	0.162***
	(0.0129)	(0.0102)	(0.0101)	(0.0109)	(0.00956)	(0.0106)
Composition Effect (Δ_X)	0.0397	0.0252	0.0373**	0.0923***	0.0630**	0.0213
	(0.0212)	(0.0147)	(0.0135)	(0.0189)	(0.0201)	(0.0223)
Wage Structure Effect (Δ_S)	0.148***	0.194***	0.206***	0.0674**	0.108***	0.141***
	(0.0228)	(0.0160)	(0.0136)	(0.0218)	(0.0205)	(0.0215)
Observations	12705	12705	12705	13274	13274	13274

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 13: Detailed Decomposition of Gender Gap in Gross Hourly Wage (Austria, 2004-2006)

Quartile	q_{75}	q_{50}	q_{25}	q_{75}	q_{50}	q_{25}
Aggregate	*Wage Structure Effect*			*Composition Effect*		
Pure Effect	0.157***	0.205***	0.216***	0.0350	0.0224	0.0283*
	(0.0179)	(0.0134)	(0.0120)	(0.0229)	(0.0167)	(0.0137)
Error	-0.0177	-0.00860	0.00223	0.00465	0.00282	0.00906
	(0.0117)	(0.00697)	(0.00681)	(0.0141)	(0.0107)	(0.00901)
Detailed	*Pure Wage Structure Effect*			*Pure Composition Effect*		
Service	0.0486*	0.000832	-0.00604	0.00402	0.00458	0.00429
	(0.0244)	(0.0149)	(0.0158)	(0.00449)	(0.00318)	(0.00301)
Abstract	0.0221	-0.0101	-0.0193	0.00647	0.00630	0.00554
	(0.0160)	(0.0138)	(0.0146)	(0.00471)	(0.00444)	(0.00407)
Routine	0.0402	0.00606	0.0244	0.00212	-0.00117	0.00162
	(0.0207)	(0.0145)	(0.0142)	(0.00251)	(0.00229)	(0.00261)
Offshoring	0.0222	0.0109	0.0142	-0.00642	-0.00393	-0.00122
	(0.0194)	(0.0168)	(0.0181)	(0.00338)	(0.00319)	(0.00356)
Education	-0.0139	-0.0215*	-0.00559	-0.00283	0.00113	0.00627
	(0.0133)	(0.00972)	(0.0101)	(0.00606)	(0.00450)	(0.00376)
Sector	-0.00593	-0.0181	-0.0178	-0.00280	-0.0138	-0.00991
	(0.0218)	(0.0164)	(0.0163)	(0.0110)	(0.00862)	(0.00802)
Personal Char.	0.00345	0.0374	0.0822**	0.0320***	0.0193***	0.0114***
	(0.0311)	(0.0202)	(0.0284)	(0.00495)	(0.00306)	(0.00281)
Job Char.	0.0598	-0.0494	-0.106	-0.0236***	-0.0125*	-0.00183
	(0.0518)	(0.0472)	(0.0744)	(0.00662)	(0.00612)	(0.00593)
Constant	-0.0711	0.238*	0.189	-	-	-
	(0.154)	(0.120)	(0.122)			
Observations	12705	12705	12705	11584	11584	11584

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 14: Detailed Decomposition of Gender Gap in Gross Hourly Wage (Austria, 2014-2016)

Quartile	q_{75}	q_{50}	q_{25}	q_{75}	q_{50}	q_{25}
Aggregate	*Wage Structure Effect*			*Composition Effect*		
Pure Effect	0.124***	0.152***	0.178***	0.0754**	0.0785**	0.0360
	(0.0141)	(0.0168)	(0.0188)	(0.0243)	(0.0260)	(0.0283)
Error	-0.0568***	-0.0445**	-0.0378**	0.0170	-0.0155	-0.0147
	(0.0149)	(0.0144)	(0.0144)	(0.0151)	(0.0155)	(0.0161)
Detailed	*Pure Wage Structure Effect*			*Pure Composition Effect*		
Service	0.00941	-0.0129	0.0335	0.00236	0.00979	-0.0151
	(0.0166)	(0.0208)	(0.0188)	(0.00672)	(0.00922)	(0.0109)
Abstract	0.0125	-0.0334**	-0.0291	0.0347***	0.0455***	0.0362***
	(0.0129)	(0.0126)	(0.0161)	(0.00925)	(0.0115)	(0.0105)
Routine	-0.0205	-0.00761	0.0487	0.00121	0.000277	0.00276
	(0.0263)	(0.0311)	(0.0286)	(0.00226)	(0.00276)	(0.00296)
Offshoring	-0.00394	-0.0154	0.0294	-0.00207	-0.00824*	-0.00142
	(0.0191)	(0.0233)	(0.0209)	(0.00262)	(0.00393)	(0.00321)
Education	0.0165	-0.0325	-0.0267	-0.000828	0.00311	0.00941
	(0.0169)	(0.0177)	(0.0185)	(0.00513)	(0.00761)	(0.00728)
Sector	-0.0781**	-0.00900	-0.0404	0.0220	0.0160	-0.0248
	(0.0303)	(0.0361)	(0.0431)	(0.0125)	(0.0135)	(0.0148)
Personal Char.	0.000985	-0.0514	0.00434	0.0203***	0.0183**	0.0172***
	(0.0290)	(0.0391)	(0.0419)	(0.00561)	(0.00592)	(0.00456)
Job Char.	0.0243	0.0827	0.00482	-0.0176*	-0.00881	-0.0104
	(0.0587)	(0.0444)	(0.0653)	(0.00798)	(0.00811)	(0.00991)
Constant	0.133	0.384*	0.140	-	-	-
	(0.135)	(0.163)	(0.176)			
Observations	13274	13274	13274	13284	13284	13284

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 15: Aggregate Decomposition of the Gender Gap in Gross Hourly Wage (Italy)

	2004-2006			*2014-2016*		
Quartile	q_{75}	q_{50}	q_{25}	q_{75}	q_{50}	q_{25}
Overall Change (Δ_O)	0.0348***	0.0593***	0.0794***	0.0415***	0.0573***	0.0574***
	(0.00903)	(0.00619)	(0.00741)	(0.00649)	(0.00582)	(0.00637)
Composition Effect (Δ_X)	-0.0551***	-0.0236*	0.00778	0.00881	0.00574	0.00585
	(0.0151)	(0.00978)	(0.00797)	(0.0139)	(0.00982)	(0.0107)
Wage Structure Effect (Δ_S)	0.0899***	0.0829***	0.0717***	0.0327*	0.0516***	0.0516***
	(0.0141)	(0.0109)	(0.00915)	(0.0152)	(0.00975)	(0.0107)
Observations	41653	41653	41653	33691	33691	33691

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 16: Detailed Decomposition of Gender Gap in Gross Hourly Wage (Italy, 2004-2006)

Quartile	q_{75}	q_{50}	q_{25}	q_{75}	q_{50}	q_{25}
Aggregate	*Wage Structure Effect*			*Composition Effect*		
Pure Effect	0.0975***	0.0893***	0.0741***	-0.0537**	-0.0207*	0.0138
	(0.0108)	(0.00871)	(0.00748)	(0.0181)	(0.0104)	(0.00710)
Error	-0.00768	-0.00649	-0.00240	-0.00137	-0.00283	-0.00601
	(0.00754)	(0.00582)	(0.00422)	(0.00897)	(0.00701)	(0.00593)
Detailed	*Pure Wage Structure Effect*			*Pure Composition Effect*		
Service	0.0359*	0.0242	0.00709	0.00322	-0.00658*	-0.00475
	(0.0147)	(0.0129)	(0.0106)	(0.00378)	(0.00334)	(0.00314)
Abstract	0.00339	-0.0285***	-0.0275**	-0.000271	-0.000278	-0.000230
	(0.0104)	(0.00797)	(0.00873)	(0.00198)	(0.00195)	(0.00168)
Routine	0.0282*	0.0215*	0.00880	0.0000528	0.000596	0.000286
	(0.0129)	(0.00917)	(0.00845)	(0.000456)	(0.000870)	(0.000470)
Offshoring	0.0335***	0.00877	0.00372	0.0000824	0.0000899	0.0000439
	(0.0101)	(0.00704)	(0.00742)	(0.000454)	(0.000468)	(0.000368)
Education	0.0173	0.0194	-0.00335	-0.0254***	-0.0223***	-0.0117***
	(0.0131)	(0.0109)	(0.00856)	(0.00477)	(0.00367)	(0.00238)
Sector	-0.0123	-0.0496***	-0.0290**	-0.0147	-0.0125*	0.00384
	(0.0195)	(0.0111)	(0.0111)	(0.00992)	(0.00570)	(0.00477)
Personal Char.	0.0287	-0.00774	0.0271	0.0260***	0.0222***	0.0179***
	(0.0228)	(0.0142)	(0.0163)	(0.00435)	(0.00331)	(0.00255)
Job Char.	0.0342	0.00213	0.0398	-0.0416***	-0.0137***	-0.000255
	(0.0245)	(0.0257)	(0.0263)	(0.00456)	(0.00289)	(0.00278)
Constant	-0.170	0.122	0.112	-	-	-
	(0.0867)	(0.0630)	(0.0631)			
Observations	41653	41653	41653	35824	35824	35824

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

Table 17: Detailed Decomposition of Gender Gap in Gross Hourly Wage (Italy, 2014-2016)

Quartile	q_{75}	q_{50}	q_{25}	q_{75}	q_{50}	q_{25}
Aggregate	*Wage Structure Effect*			*Composition Effect*		
Pure Effect	0.0655***	0.0761***	0.0681***	0.0100	0.00531	0.0115
	(0.0103)	(0.00772)	(0.00888)	(0.0179)	(0.0124)	(0.0144)
Error	-0.0329***	-0.0245***	-0.0165**	-0.00122	0.000429	-0.00566
	(0.00963)	(0.00660)	(0.00541)	(0.00998)	(0.00774)	(0.00864)
Detailed	*Pure Wage Structure Effect*			*Pure Composition Effect*		
Service	-0.0137	0.00232	0.00603	0.00801	-0.00158	-0.00233
	(0.0167)	(0.0121)	(0.0134)	(0.00698)	(0.00474)	(0.00411)
Abstract	-0.00473	-0.0108	-0.0120	0.0161***	0.0138***	0.0118***
	(0.00936)	(0.00828)	(0.00916)	(0.00437)	(0.00396)	(0.00355)
Routine	-0.0169	0.00134	-0.0169	0.0000392	0.00208	-0.0000715
	(0.0210)	(0.0160)	(0.0148)	(0.00190)	(0.00160)	(0.00142)
Offshoring	0.0142	-0.00202	-0.0142	0.000340	-0.000153	-0.000473
	(0.0166)	(0.0120)	(0.0119)	(0.00134)	(0.00106)	(0.000850)
Education	0.0159	0.00306	-0.00375	-0.0272***	-0.0200***	-0.0143***
	(0.0181)	(0.0108)	(0.0116)	(0.00497)	(0.00377)	(0.00349)
Sector	-0.0294	-0.0245*	-0.0524***	0.0118	0.0148	0.0209
	(0.0179)	(0.0110)	(0.0137)	(0.0129)	(0.00919)	(0.0115)
Personal Char.	-0.00736	0.0254	0.0220	0.0162***	0.0118***	0.0106***
	(0.0262)	(0.0199)	(0.0202)	(0.00285)	(0.00202)	(0.00205)
Job Char.	-0.0477	0.00401	0.0525	-0.0233***	-0.0242***	-0.0177***
	(0.0247)	(0.0267)	(0.0341)	(0.00430)	(0.00303)	(0.00290)
Constant	0.180	0.0827	0.155	-	-	-
	(0.0949)	(0.0786)	(0.0806)			
Observations	33691	33691	33691	33396	33396	33396

Notes: Bootstrapped standard errors (100 replications) in parentheses; (*) $p < 0.05$, (**) $p < 0.01$, (***) $p < 0.001$.
Source: Authors' calculations based on O*NET and EU-SILC data.

9.3 Other Tables

Table 18: Occupation Groups: Aggregation of ISCO-88 and ISCO-08

ISCO-88	ISCO-08
Managers	
Legislators and senior officials (11); Corporate managers(11); Managers of small enterprises(13);	Chief executives, senior officials and legislators (11); Administrative and Commercial Managers (12); Production and Specialized Services Managers (13); Hospitality, Retail and Other Services Manager (14);
Science,Engineering,IT Professionals	
Physical, mathematical and engineering science professionals (21);	Science and Engineering Professionals (21); Information and Communications Technology Professionals (25);
Health Professionals	
Life science and health professionals (22);	Health Professionals (22);
Teaching Professionals	
Teaching professionals (23); Teaching associate professionals (33);	Teaching Professionals (23);
Business,Legal,Cultural Professionals	
Other professionals (24);	Business and Administration Professionals (24); Legal, social and cultural professionals (26);
Science,Engineering,IT Associate Professionals	
Physical and engineering science associate professionals (31);	Science and Engineering Associate Professionals (31); Information and Communications Technicians (35);
Health Associate Professionals	
Life science and health associate professionals (32);	Health associate professionals (32);
Other Associate Professionals	
Other associate professionals (34);	Business and Administration Associate Professionals (33); Legal, Social, Cultural Professionals (34);
Office Clerks	
Office clerks (41);	General and Keyboard Clerks (41); Numerical and Material Recording Clerks (43); Other Clerical Support Workers (44);
Customer Service Clerks	
Customer Services Clerks (42);	Customer Services Clerks (42);
Service, Personal Care, Security Workers	

Table 18 continued

ISCO-88	ISCO-08
Personal and protective services workers (51);	Personal Services Workers (51); Personal Care Workers (53); Protective Services Workers (54);
Sales Workers	
Models, salespersons and demonstrators (52);	Sales Workers (52);
Skilled Agricultural & Fishery Workers	
Skilled agricultural and fishery workers (8cm);	Skilled Agricultural Workers (61); Skilled Forestry, Fishery and Hunting Workers (62); Subsistence Farmers, Fishers, Hunters and Gatherers (63);
Building Workers	
Extraction and building trades workers (71);	Building and Related Trades Workers (excluding Electricians) (71);
Metal & Machinery Workers	
Metal, machinery and related trades workers (72);	Metal, Machinery and Related Trades Workers (72); Electrical and Electronic Trades Workers (74);
Precision, Handicraft & Printing Workers	
Precision, handicraft, craft printing and related trades workers (73);	Handicraft and Printing Workers (73);
Food Processing, Wood & Other Workers	
Other craft and related trades workers (74);	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers (75);
Stationary Plant Machine Operators & Assemblers	
Stationary plant and related operators (81); Machine operators and assemblers (82);	Stationary Plant and Machine Operators (81); Assemblers (82);
Drivers & Mobile Plant Operators	
Drivers and mobile plant operators (83);	Drivers and Mobile Plant Operators (83);
Elementary Sales & Service Laborers	
Sales and services elementary occupations (91);	Cleaners and Helpers (91); Food Preparation Assistants (94); Street and Related Sales and Services Workers (95); Refuse Workers and Other Elementary Workers (96);
Agricultural & Fishery Laborers	
Agricultural, fishery and related labourers (92);	Agricultural, Forestry, Fishery Laborers (92);
Mining, Manufacturing & Transporting Laborers	
Labourers in mining, construction, manufacturing and transport (93);	Laborers in Mining, Construction, Manufacturing and Transport (93);

Source: Authors' representation using the official ISCO classification of the International Labor Organization (ILO).

Table 19: Industry Groups: Aggregation of NACE Rev. 1.1 and NACE Rev. 2

NACE Rev. 1.1	NACE Rev. 2
Manfacturing & Production	
Agriculture, hunting and forestry (A); Fishing (B); Mining and quarrying (*C*); Manufacturing (D); Electricity, gas and water supply (E);	Agriculture, forestry and fishing (A); Mining and quarrying (B); Manufacturing (*C*); Electricity, gas, steam and air conditioning supply (D); Water supply; sewerage, waste management and remediation activities (E);
Construction	
Construction (F);	Construction (F);
Wholesale & Retail	
Wholesale and retail trade(G);	Wholesale and retail trade; repair of motor vehicles and motorcycles (G);
Transport	
Transport, storage and communication (I);	Transportation and storage (H);
Hotels & Accomodation	
Hotels and restaurants (H);	Accommodation and food service activities (I);
Services, R&D, IT	
Financial intermediation (J); Real estate, renting and business activities (K);	Financial intermediation (J); Real estate, renting and business activities (K);
Public Administration	
Public administration and defence; compulsory social security (L);	Public administration and defence; compulsory social security (L);
Education	
Education (M);	Education (P);
Health	
Health and social work (N);	Human health and social work activities (Q)
Other services	
Other community, social and personal service activities (O); Activities of households (P); Extra-territorial organizations and bodies (Q);	Arts, entertainment and recreation ®; Other service activities (S); Activities of households as employers (T); Activities of extraterritorial organisations and bodies (U);

Source: Authors' own representation using the official NACE classification for the EU.

Table 20: O*NET Task Indicator by Occupational Task Measure

Routine	Operation Monitoring; Operation and Control; Equipment Maintenance; Quality Control Analysis; Inspecting Equipment, Structure or Material; Estimating the Quantifiable Characteristics of Products; Arm-Hand Steadiness; Manual Dexterity; Finger Dexterity; Reaction Time; Wrist-Finger Speed; Speed of Limb Movement; Static Strength; Explosive Strength; Dynamic Strength; Trunk Strength;
Service	Social Perceptiveness; Service Orientation; Assisting and Caring for Others; Establishing and Maintaining Interpersonal Relationships; Resolving Conflicts and Negotiating with Others; Selling or Influencing Others; Active Listening; Performing for or Working Directly with the Public;
Abstract	Originality; Critical Thinking; Active Learning; Learning Strategies; Monitoring; Coordination; Negotiation; Instructing; Persuasion; Judgment and Decision Making; Systems Analysis; Systems Evaluation; Time Management; Management of Personnel Resources; Management of Material Resources; Management of Financial Resources ; Judging the Qualities of Things, Services or People; Making Decisions and Solving Problems; Thinking Creatively; Developing Objectives and Strategies; Scheduling Work and Activities; Organizing Planning and Prioritizing Work; Drafting Laying Out and Specifying Technical Devices, Parts and Equipment; Interpreting the Meaning of Information for Others; Communicating with Supervisors, Peers or Subordinates; Communicating with Persons Outside the Organization; Coordinating the Work and Activities of Others; Developing and Building Teams; Training and Teaching Others; Guiding Directing and Motivating Staffing Organizational Units; Monitoring and Controlling Resources; Oral Comprehension; Written Comprehension; Oral Expression ; Written Expression; Fluency of Ideas; Problem Sensitivity; Deductive Reasoning; Inductive Reasoning; Mathematical Reasoning; Information Ordering; Category Flexibility; Number Facility; Speed of Closure; Perceptual Speed; Visualization; Selective Attention; Time Sharing; Speech Clarity; Speech Recognition; Reading Comprehension; Flexibility of Closure; Writing; Speaking; Mathematics; Science; Complex Problem Solving; Operations Analysis; Technology Design; Equipment Selection; Programming; Troubleshooting; Getting Information; Monitor Processes, Materials or Surroundings; Processing Information; Evaluating Information to Determine Compliance With Standards; Analyzing Data or Information; Updating and Using Relevant Knowledge; Interacting With Computers;
Offshorability	Assisting and Caring for Others; Face to Face Discussions; Performing for or Working Directly with the Public; Establishing and Maintaining Interpersonal Relationships; Coaching and Developing Others; Inspecting Equipment, Structures or Material; Handling and Moving Objects; Controlling Machines and Processes; Operating Vehicles and Mechanized Devices; Repairing and Maintaining Electronic Devices; Repairing and Maintaining Mechanic Devices;

Note: Author's own representation using the O*NET database.

9.4 German Abstract

Auf der Grundlage von EU-SILC-Mikrodaten ermittle ich den Beitrag des Anstiegs der Nutzungsintensität digitaler Technologien am Arbeitsplatz zur Lohnungleichheit sowie zum Lohngefälle zwischen den Geschlechtern in den letzten Jahren. In Anlehnung an die bisherige Forschung wende ich ein von Autor, Levy, and Murnane (2003) entworfenes Konzept an, das Berufe in Bezug auf ihre Aufgaben definiert. Dieser Ansatz wird verwendet um Indikatoren für die Merkmale der Berufe zu konstruieren, die den technologischen Wandel erfassen. Die Quantifizierung der Auswirkungen verschiedener Faktoren auf die Ungleichheitsmaße erfolgt mit Hilfe einer von Fortin, Firpo, and Lemieux (2011) entwickelten kontrafaktischen Zerlegungsmethodik. Die wichtige Rolle der Digitalisierung wird durch die Resultate bestätigt. Die Auswirkungen unterscheiden sich sowohl zwischen den Geschlechtern als auch entlang der Lohnverteilung erheblich. Während Frauen am unteren Ende der Verteilung negative Konsequenzen erfahren, ist der Effekt für weibliche Arbeitnehmer in höheren Dezilen der Lohnverteilung gering. Bei Männern ist der Effekt entlang der Verteilung sehr unterschiedlich ausgeprägt, zeigt jedoch eine weniger Ungleichheitsfördernde Auswirkung. Die Zerlegung des geschlechtsspezifischen Lohngefälles, des sogenannten *Gender Wage Gaps*, deutet auf diskriminierungsverändernde Auswirkungen des technologischen Wandels hin.

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