Gender wage gap and the role of skills: evidence from PIAAC dataset

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Abstract:
Our paper makes a first attempt to address the impact of skills and skill use in the analysis of the gender wage gap using the PIAAC dataset. Using the case of Austria, we show that skill use as well as the skill match play an important role with regard to wage regressions of men as well as women. When we take skills into account in the gender wage gap analysis, the unexplained part of the gender wage gap is reduced by almost 4 percentage points along the whole wage distribution. Our results suggest that skill use and match play a crucial role in explaining the gender wage gap. Additionally, we show, that the self-selection problem biases the results, in particular in the lower and middle parts of the wage distribution and that we should control for it, although the effect is small. When we additionally consider discretionary bonus payments, we find that the unexplained part in the gender wage gap increases, especially in the upper part of the wage distribution.

Keywords:
Gender wage gap, skills, Austria

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Gender Wage Gap and the Role of Skills and Tasks: Evidence from the PIAAC Data Set*

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Abstract

We analyze the gender differences in skills, tasks and skill matching of workers, and the impact of these factors on the gender wage gap, using the Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC). We show that data on these characteristics, not available in traditional data sets, explain a substantial part of the gender wage gap. Based on our methodology, the unexplained part of the gender wage gap is reduced by 6 to 9 percentage points across the whole wage distribution when we add skill and occupational task variables and control for sample selection. We show that this result stems from gender differences in returns to tasks and skills, and gender differences in skill endowments and occupational tasks.
JEL Classification: J31, J71
Keywords: gender wage gap, cognitive skills, tasks, Austria

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1. Introduction

The gender wage gap is one of the most widely discussed topics in the area of possible wage discrimination. Although many forms of discrimination exist with respect to gender, we focus on the potential for discrimination in the labor market. It is well established that discrimination in other aspects of society, such as education, may additionally lead to discrimination in the labor market. However, this is not the topic of our analysis.

Our focus concerns the extent to which the gender wage gap can be explained by differences in endowments of, and returns to, particular skills and tasks at work between the genders. To achieve this goal, we use a data set which encompasses not only detailed information about cognitive skills but also comprehensive descriptions of tasks at work, or in other words, whether and which skills are used in the workplace. We are interested in whether differences in skills and tasks affect the size of the gender gap.

Some scholars, e.g., Kunze (2008), warn against interpreting the unexplained gender wage gap as discrimination, since typically one cannot measure productivity differences precisely enough or assume that those differences themselves are not an outcome of discriminatory behavior. To ensure the comparability of our results with previous studies, we study the gender wage gap using a decomposition method. However, we remain cautious when interpreting our results.

In their overview, Weichselbaumer and Winter-Ebmer (2005) show that there has been a significant reduction in the gender wage gap over the past 30 years in OECD countries, and that most of the gender wage gap stems from differences in characteristics between men and women. This indicates that differences in wages between the genders in the labor market are probably smaller than differences in other areas of society. Moreover, access to more reliable data and more sophisticated econometric techniques allows us to look more closely at the gap than was possible 30 years ago. Indeed, it may be the case that ever-better estimation techniques partly explain why the gender wage gap is closing.

Nevertheless, the question concerning differences between the genders in the labor market is not an easy one. High-quality data are needed to ensure that all valid characteristics of workers can be covered. For that reason, in our study we consider some factors affecting wages which have not been covered in previous analyses, using a new data set.

It has often been argued that occupational segregation by gender is the main driver of the difference in pay for men and women, for example, by Blau and Kahn (2000). Even though occupational segregation has fallen in most developed countries over recent decades, according to Blau et al. (2013), and there has also been a beneficial effect of technology on the difference between male and female earnings (see, e.g., Black and Spitz-Oener 2010), the gender wage gap is still prevalent. Similar conclusions can be drawn from Yamaguchi (2018) who finds that narrowing gender gap is result of technological change, which differentially affects females and males. It is noteworthy that, according to Goldin (2014), the gender wage gap is especially prominent within narrowly defined occupations rather than across the whole range of occupations. Autor and Handel (2013) show that tasks in the US vary substantially within certain occupations in the context of gender and race. If this is indeed the case, controlling for tasks or skills could further explain the gender wage gap in Austria. This is the possibility that motivates our paper.

It is particularly difficult to find data on workers' skills and skill use at work, whether workers are overqualified or underqualified and other characteristics that are clearly decisive for productivity and, in turn, on earned wages. Among others, Hanushek et al. (2015), in their widely cited work, used the PIAAC data to analyze returns to skills of workers, but without a detailed study of gender-specific differences. Failure to include such variables in the gender wage gap analysis leads to a bias in the unexplained part of the gender wage gap, and automatically results in an incorrect estimate of potential wage differences.

Additionally, many studies have shown that the unexplained gender wage gap is not consistent across the wage distribution. Most papers find that it increases across the wage distribution. In Austria and Germany, for instance, it is hypothesized that this stems from binding collective bargaining contracts at the lower end of the wage distribution. Particular skills and tasks at work at different wage levels can also partly explain this finding. On the other hand, the important issue of selection in the workforce affects the estimation of the gender gap at the lower end of the distribution (as it does at the opposite end). Without controlling for sample selection, we could compare a representative sample of males with the most productive females, which would lead to underestimation of the size of the wage gap.

In the light of the above observations, we make a first attempt to include variables such as the skills and tasks of workers, the level of overqualification or underqualification and the flexibility of work for families with small children, in order to account for otherwise excluded characteristics. In fact, these characteristics have not previously been covered in studies of the gender wage gap in Austria. Taking these factors into account, we show that the estimated wage gap is much smaller than reported in previous studies, once specific skills, their utilization and work flexibility are controlled for. Moreover, we control for the selection of individuals in the workforce and show that the wage gap increases slightly due to sample selection. We exploit the data set for a single country, as cross-country differences in labor-market participation or returns to skills (compare, e.g., Hanushek et al. 2017) could bias the results. This issue is discussed in more detail later.

More generally, further research regarding gender-specific skills and tasks and their impact on the gender wage gap based on the PIAAC data set is highly desirable, as it allows skills and their utilization, (tasks performed at work) to be directly controlled for. To the best of our knowledge, this is the first study to exploit this data set in the context of gender-specific skills and tasks.

This paper is structured as follows. The next section provides a brief overview of the gender gap literature with a focus on previous estimates of the gender gap in Austria. Section 3 presents theoretical foundations, while section 4 presents the data set and the empirical approach. Section 5 presents the results, and section 6 concludes the paper.

2. Literature Overview

While different studies often concentrate on different features with regard to the gender wage gap, there are several aspects that are generally common to all of them. The first involves Blinder (1973) and Oaxaca (1973)-type decomposition, which can be described as a method of splitting the unadjusted gender wage gap into two parts, where one part is described as the explained part and the remainder is the unexplained part. The explained part implies that part of the gap that can be positively ascribed to differences in certain characteristics, while the other part is commonly interpreted as discrimination.

The Blinder and Oaxaca approach is based on human capital theory, which states that wages are tied to productivity, so that an observed male-female wage gap should be explained by differences in productivity between men and women. As a result, most studies consider factors affecting productivity, such as education, work experience and tenure.

Any discussion of previous studies can by no means be definitive or exhaustive. Nevertheless, several trends and recent results can be summarized. Different scholars and institutions choose different factors to add to the basic human capital and productivity characteristics which appear in almost all studies. The choice of factors depends on the specific inquiry, and can increase the part that can be explained through regression analyses. Recently, therefore, more detailed studies have tended to exhibit smaller unexplained parts than either earlier works or all-encompassing international analyses.

Boll and Leppin (2015) show that in Germany, the unadjusted gender wage gap of (up to) 23.9% leaves an unexplained part of 2.3% when various characteristics are controlled for. Differences in experience, working hours, work status, sector and the migration background of men and women represent the five factors that explain most of the gender wage gap in Germany. The authors further break the gap down across the wage distribution, showing that, while women in the bottom quantiles experience positive discrimination of 9% (probably through collective agreements), women at the top of the distribution experience an unexplained wage gap of 8%. Blau and Kahn (2016) paint a similar picture for the US.

In a cross-country study, Boll et al. (2016) add variables such as overeducation, perceived health, existence of a supervisory position and information on a partner's labor-market characteristics (if available), to the usual characteristics. They find an unadjusted cross-country gap of 18.4%, which they break down into an 11.1% unexplained gap and a 7.2% explained gap. Although on this cross-country basis the unexplained part still makes up the majority of the gap, several countries, namely Austria, France, Norway, Serbia and Switzerland, exhibit an unexplained gap of less than 5%.

Cross-country analyses of the gender wage gap exhibit specific problems. Boll et al. (2016), along with other studies, such as Tijdens et al. (2012), draw attention to the fact that low job-market participation rates among females correlate with a small gender wage gap. This is explained by the selection process that results in lower job-market participation among females. In countries with low female participation rates, only the most educated and qualified women participate, finding themselves in relatively well-paid jobs.

The question concerning female labor-force participation often hinges on national family policies. A large part of the gender gap literature focuses on the impact of the 'children factor' on parents' wages, which is often called the family wage gap. Meurs et al. (2010) examine the impact of child-related career interruptions on women's wages, whereas studies such as Angelov et al. (2016) have shown no evidence of the direct impact of children on the wages of mothers. Furthermore, Meurs et al. (2010) similarly conclude that it is not the mere presence of a child that has an impact on women's wages, but child-related career interruptions.

Since having a child may require more job flexibility, especially in countries where the provision of public childcare is limited, it is often argued that this factor influences wages. Goldin (2014), when investigating BA graduates working full-time and for an entire year, found that most of the gender gap (68%) was due to differences within occupations. Furthermore, she demonstrated that occupations that show nonlinearity in earnings with respect to the time worked, also show the highest gender pay gap. Moreover, recent research by Deschacht et al. (2017) suggests one more channel for occupational sorting. Deschacht et al. (2017) report that female young professionals have a less pronounced preference for jobs implying a promotion in terms of job content and that this effect is mediated by the greater risk aversion and anticipated gender discrimination among women.

Autor and Handel (2013) show that tasks in the US vary substantially between gender and race within occupations. When we combine these findings with the results of Goldin (2014), we can conclude that the differences in skill use at work could explain wage differences between genders. To the best of our knowledge, no empirical literature exists at present that explicitly measures the effects of skill use at work on the gender wage gap.

This paper is also closely related to the literature on the returns to cognitive skills and tasks at work. Hanushek et al. (2015; 2017) show, using the PIAAC data set, that returns to literacy and numeracy skills can be an important predictor of wage levels. In addition, Anspal

(2015), who focus on gender-specific returns to cognitive skills, show for the case of Estonia that numeracy and literacy skills have an impact on the size of the gender gap. However, they do not consider the actual skill use at work.

Previous literature has given attention to the issue of the gender gap with respect to cognitive skills, e.g., mathematics skills (see, e.g., Heckman et al. 2006, Fortin 2008, Blau and Kahn 2016). At the same time, Acemoglu and Autor (2011) and Firpo et al. (2010), among others, point to tasks at work being a more important driver of wages. Acemoglu and Autor (2011) point out that

> "(...) a skill is a worker's endowment of capabilities for performing various tasks. Workers apply their skill endowments to tasks in exchange for wages, and skills applied to tasks produce output. The distinction between skills and tasks becomes particularly relevant when workers of a given skill level can perform a variety of tasks (...)"

and thus points to the need to control for both skills and tasks at work, while estimating the returns. The combination of gender-specific cognitive skills and tasks is therefore an important factor in determining the size of the wage difference between males and females.

Although our main focus is on the gender-specific endowments and returns affecting the gender gap, for the sake of completeness we link our results to some previous estimates for Austria. Empirical studies with regard to the gender wage gap in Austria are manifold. The most recent papers for Austria (data used, results and methodology) are summarized in Table 1. All these studies face some data issues regarding unobserved characteristics such as the skills of workers, individuals with (small) children and job flexibility, but their results indicate that the unexplained gender wage gap lies between 12% and 20%.

	Dep. variable	Controls	Unexplained gap	Method	Remarks
Böheim et al. (2005)	net earnings per month	education, experience, position, white-collar, hours worked, occup. segregation, family status, nationality	15.5% in 1997	quantile regression, Oaxaca-Blinder	increase over the wage distribution
Böheim et al. (2007)	net earnings per month (FT equivalent)	education, experience, position, career interruptions, white collar, industry, family status, nationality, city size, region	14% in 1997	quantile regression, Oaxaca-Blinder	decrease in discrimination over time
Grünberger et al. (2009)	gross hourly wages (FT)	education, experience, occupation, worker status, industry, family status, nationality, region	12% in 2006	Mincer wage regression	increase over the wage distribution
Böheim et al. (2013a)	gross hourly wages (FT)	education, experience, occupation, career interruptions, length of maternity leave, worker status, industry, firm size, family status, nationality, city size, region	14% in 2007	quantile regression (Melly (2006))	increase over the wage distribution
Böheim et al. (2013b)	gross hourly wage	education, experience, tenure, length of interruptions, family status, citizenship, population density, worker status, firm size, firm characteristics (age, female/male, turnover)	16% in 2007	Oaxaca-Blinder	reduction between 2002 and 2007
Grandner and Gstach (2015)	gross hourly wage	education, experience, country of birth, age, firm size, temp. job, public sector, family status	20% in 2008	quantile regression, Machado and Mata (2005)	constant over the wage distribution
Böheim et al. (2017)	gross hourly wage	education, experience, children, urbanization, age, sector, position, married, country of birth	10,7% in 2015	Oaxaca-Blinder, selection model	reduction between 2005 and 2015

Table 1: Literature overview for Austria

3. Theoretical Considerations

The conceptual model of how tasks affect wages can be derived from Autor and Handel (2013). According to the standard Roy (1951) model, workers self-select into occupations based on their human capital. Given this non-random assignment of workers to tasks, it is not straightforward how to determine average returns to tasks. Autor and Handel (2013) propose that the underlying selection problem can be mitigated by either allowing the returns to tasks to vary by occupations or by using the fact that we should observe nonzero covariances between occupation-level tasks returns and the tasks endowments of workers who self-select into these occupations. Empirically it means inclusion of interaction terms between the individual task profiles and occupation-means of tasks profiles. The signs of the interaction terms can additionally be interpreted as *comparative* or *absolute* advantage of workers with regards to tasks. Comparative advantage means that workers self-select into each occupation and the interaction terms should show positive covariance. On the other hand, in case of absolute advantage some workers are good in all tasks and selected positively into some occupations, while others select negatively - resulting in negative correlations between individual-level and occupation-level tasks.

In the context of wage differences between genders we should allow for several possibilities: firstly, male and female workers may have different efficiencies for performing the same tasks - or in other words are endowed with different task abilities. Secondly, the returns to tasks may be different for males and females within the same occupations. Thirdly, females and males may self-select into occupations in a different manner. It is assumed, that workers are paid their marginal product. A specification, which accounts for these factors can be summarized as

$$w_i^G = \alpha_j + \sum_{k=1}^{K} \lambda_{jk}^G \phi_{ik}^G + \mu_i, \tag{1}$$

where index $G = M, F$ denotes the gender, w_i is the log-wage, λ_{jk}^G are the occupation-specific task returns and ϕ_{ik}^G are the skills' endowments applied to these tasks. If self-selection to occupations is indeed present, we should observe non-zero covariances between occupation-level and individual-level task variables. Following Autor and Handel (2013), we can specify this equation as

$$w_{ij}^G = \alpha_j^G + \beta_k^G T_i^G + \delta_k^G \bar{T}_j + \gamma_k^G T_i^G \times \bar{T}_j + \varepsilon_{ij}^G, \tag{2}$$

where T_i denotes the individual-level tasks and $\bar{T}_j$ are the occupation-level tasks. Parameter γ_k measures the covariances between the two, that is, the necessary condition for the data to be consistent with self-selection of workers.

4. Data and Estimation

4.1. The Empirical Approach

We firstly use quantile regressions to estimate the model as described in Equation 2, for each gender separately. These results will be used to estimate the size of the gender wage gap. We estimate the gender wage gap using the counterfactual distributions approach, as presented by Chernozhukov et al. (2013). Previous studies of the gender gap in Austria relied on the Machado and Mata (2005) approach to estimate counterfactual distributions. Improving on the existing literature also allows us to study the contribution made by specific covariates in different parts of the distribution (see, e.g., Depalo et al. 2015). Following the example of Chernozhukov et al. (2013), let $j = 0, 1$ denote the subpopulation of men ($j = 0$) and the subpopulation of women ($j = 1$). Y_j denotes the wages, while X_j is the vector of job-relevant characteristics affecting the wages. The conditional distribution functions $F_{Y_0|X_0}(y|x)$ and $F_{Y_1|X_1}(y|x)$ describe the assignment of wages y to individuals with characteristics x. If $F_{Y<0|0>}$ and $F_{Y<1|1>}$ are the observed distributions for men and women respectively, we can denote

$$F_{Y<0|1>}(y) \equiv \int_{\chi_1} F_{Y_0|X_0}(y|x) dF_{X_1}(x) \tag{3}$$

as the counterfactual distribution function of wages that would have prevailed for women had they faced men's wage schedule, where χ_1 denotes the support for women's characteristics. This distribution is constructed by integrating the conditional distribution of wages for men with respect to the distribution of characteristics for women (Chernozhukov et al. 2013).

The difference between the wage distributions can be then decomposed according to

$$F_{Y<1|1>} - F_{Y<0|0>} = [F_{Y<1|1>} - F_{Y<0|1>}] + [F_{Y<0|1>} - F_{Y<0|0>}], \tag{4}$$

where the first term corresponds to the differences in returns, and the second term corresponds to the differences in characteristics. Under the conditional exogeneity assumption, the counterfactual effect can be interpreted as causal.

The estimator used is the linear quantile regression estimator presented by Koenker and Bassett Jr (1978). The confidence intervals are bootstrapped, using the asymptotic properties given by Chernozhukov et al. (2013).

A second methodological issue concerning the fact that some often-used control variables are endogenous (such as selection within certain activities, full-time work or simply a decision to start working) is an important factor. If, for instance, the reservation wage of a woman depends on her productivity, and potentially, therefore, the same factors as the observed wages, the estimates will be biased due to the sample selection. In essence, failure to correct for the sample selection means comparing the wages of a representative sample of males with a censored sample of females, where the censoring implies that the least-productive females are not observed. If this is the case, the uncorrected gender gap will be underestimated.

We therefore correct for selection within employment. Despite high labor-force participation, Austria is experiencing, in common with comparable European countries, very high part-time employment, which is typically associated with lower hourly wages: over 47% of females were working part-time in 2016, compared to the average of about 36% in the euro area[2], which can be explained by several factors:

- Traditional division of tasks in the family, i.e., females are expected to take over the major part of household and childcare obligations.

- Comparative underprovision of public childcare institutions, particularly for children aged three years or under.

[2]Among European countries, higher rates of part-time work for females in 2016 were reported only for Switzerland and the Netherlands.

- Generosity of the social system and long periods of maternity leave (up to three years).

In effect, women are more likely to stay outside the labor force or work part-time, especially if they have children, as the opportunity cost of working (that is, the loss of social benefits and additional costs associated with institutionalized childcare) could be too high. We therefore include factors affecting the reservation wage as well as childcare obligations in the selection equation.

To correct for sample selection, we apply the non-additive approach proposed recently by Arellano and Bonhomme (2017)[3]. As shown by Arellano and Bonhomme (2017), the obtained quantile regression coefficients can be subsequently used to obtain the empirical distributions as developed by Machado and Mata (2005) and Chernozhukov et al. (2013).

The method of Arellano and Bonhomme (2017) involves a three-step estimation procedure: in the first step, a consistent estimator of the propensity score $\hat{\theta}$ (in our case, for the probability of working) is estimated using maximum likelihood. In the second step, a consistent estimator of the copula parameter vector $\hat{\rho}$ is found using grid search. Lastly, given $\hat{\theta}$ and $\hat{\rho}$, for each quantile τ, $\hat{\beta}_\theta$ a consistent estimator vector of the τth quantile regression is found. We have implemented the original Matlab code of Arellano and Bonhomme (2017) in R, additionally allowing for including the survey weights in the quantile regressions' estimations. Moreover, since our explanatory variables include not only personal-levels characteristics (as is the case for Arellano and Bonhomme (2017)), but also firm-level characteristics, the Arellano and Bonhomme (2017) estimator has been adapted for choosing only personal-level characteristics in the first-stage equation. For the decomposition, we implemented the Stata *cdeco* code of Chernozhukov et al. (2013), to decompose the quantile regression coefficients from the first stage.

For identification, it is necessary to include in the propensity score estimation, variables that determine the reservation wage but do not enter the wage equation. In our case, the instruments are: age, age squared, dummy for whether a person is living with a spouse/partner and the net replacement rates obtained from the demographic characteristics of the house-

[3]Moreover, Huber and Melly (2015) have expressed doubts about the assumption of homogenous selection across the quantiles, as also visualized by Machado (2017)

hold. The influence of the welfare system on reservation wages can be quantified by the net replacement rate. The net replacement rate is one factor that influences the reservation wage of an individual, and therefore the value of leisure, directly, but it varies between different household types.

We use the replacement rates of the OECD for different household types in Austria for the year 2011. This approach is similar to using non-labor income (see, e.g., Blau and Beller 1988), which depends not only on individual characteristics, but also on household characteristics, in particular on the working status of a partner. We distinguish between single, one-earner and two-earner households that have either no children, one child or two (or more) children. The net replacement rates are defined as the proportion of net income from work that is maintained after a job loss for different household types. The net replacement rate covers not only unemployment benefits, but also housing and family benefits received by an individual if they are not working. Moreover, since the net replacement rate is continuous, it allows us to identify the first-stage equation over the whole support. Instruments included in both equations represent other demographic characteristics of an individual: education, children and migration background. Indeed, age affects the productivity of workers as well as the depreciation of their skills (Bloom and Sousa-Poza 2013, Bertoni et al. 2015), and therefore also impacts on wages. However, given the correlation between age and experience in almost 90% of our sample, inclusion of both variables in the wage regression does not reveal much additional information.

4.2. Data

We use the data set for Austria provided by the PIAAC survey, which was conducted by the OECD in 2011/12. It encompasses 4,810 individual observations, and includes detailed information about education, skills, income and family background. After filtering out observations with no information on wages, i.e., for the non-working population, our sample reduces to about 2,200 observations. In terms of the number of observations, this is smaller than the EU-SILC data set used, for instance, by Grandner and Gstach (2015), or the Austrian social security data set used by Böheim et al. (2013a), but large enough to conduct an empirical analysis. However, we must keep in mind that estimation at the tails will be less precise due to a smaller sample size, and caution is needed in forming conclusions, particularly at the upper tail of the distribution. The dependent variable in all estimations is the log of hourly wages[4].

Similarly to previous studies, detailed information about personal and job characteristics is provided. The greatest advantage of the new data set, however, is the possibility of controlling for additional, often unobserved, characteristics, such as the skills, specific tasks and skill matching of individuals.

An overview of the characteristics used in this study can be found in Table A.5, while the logged wage distributions for different genders are presented in Figure A.9, both in the Appendix. We can see that, for the total hourly wages, the wage distribution of males shifts to the right, no matter whether we use the whole sample or only those who work full-time. That said, it is observable that differences in wage distributions between females and males are lower when we restrict the sample to full-time workers.

The following paragraphs give short descriptions of the above-mentioned additional variables: skills, tasks, skill match and flexibility.

Skills. We can control for general cognitive skills of individuals measured in PIAAC, such as literacy skills and numeracy skills. Unlike, for instance, Garcia et al. (2001), who uses instrumental variables to control for unobserved skills, we can directly control for skills which affect productivity on the one hand and may also be rewarded by the employer on the other.

According to Figure 1, females on average score similarly to males when it comes to literacy skills, but significantly lower on the numeracy scale. This result is consistent with, e.g., Stoet and Geary (2018), who find that science or mathematics are much more likely to be a personal academic strength for boys than girls.

Task Profiles (skill use). We can take a closer look at task profiles that vary widely across the same occupations, as discussed by Autor and Handel (2013). To control for skill use at work, we follow Perry et al. (2014) and use the job requirements approach. The PIAAC question-

[4]To see whether the wage distribution of the PIAAC data set is representative of the Austrian wage distribution, we compare the wage data of PIAAC with the wage tax statistics of Statistics Austria (see Figure A.10 in the Appendix) and confirm that the two data sets are in close correspondence.

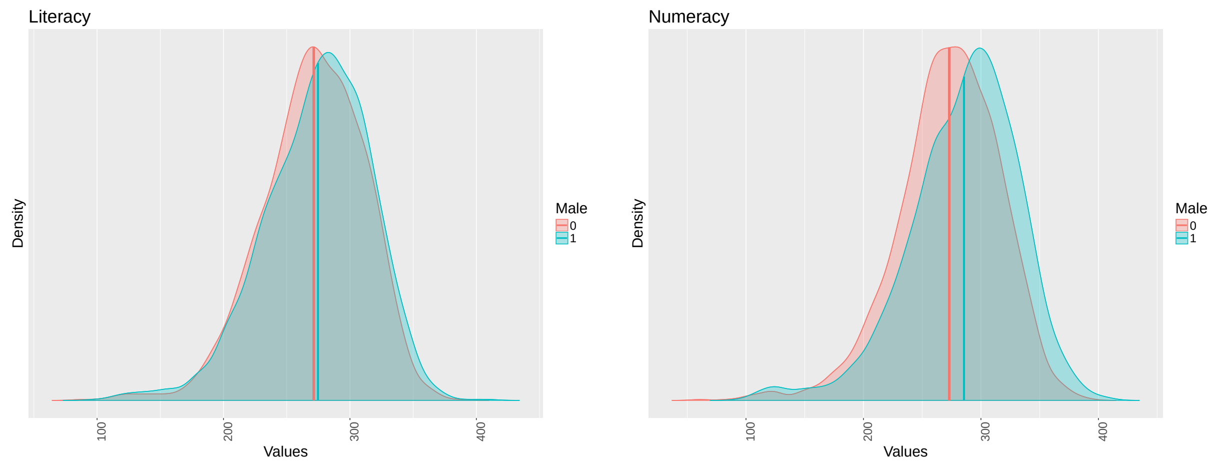


Figure 1: Cognitive skills: gender differences in Austria

naire asks participants how often they use particular skills at work. Given the participants' answers, several indices are calculated[5]. The indices are derived for several skills that are typically used at work. Some example activities for each of the indices are listed below:

- Influencing: influencing people, sales, negotiations, etc.
- Planning: planning own activities, planning others' activities, etc.
- Writing: writing articles, writing reports, filling in forms, etc.
- Numerical: calculating costs or budgets, preparing charts or tables, using advanced math or statistics, etc.
- Reading: reading letters and emails, reading professional journals, reading financial statements, etc.
- ICT: using the Internet, using Microsoft Word or spreadsheets, programming, etc.

By simply comparing the average indices for males and females, we can see that there are, on average, differences in tasks at work between genders. Figure 2 reveals that especially in

[5]Those indices are then summarized into quintiles, where the first quintile represents the 20% with the lowest skill use and the fifth quintile represents the highest values of skill use at work for a specific skill type. The mean score and standard errors are standardized with a mean of 2 and a standard error of 1 across the OECD countries participating in PIAAC.

numerical and ICT tasks, but also in most of the other tasks' variables, males tend to perform these tasks, on average, more often than females.

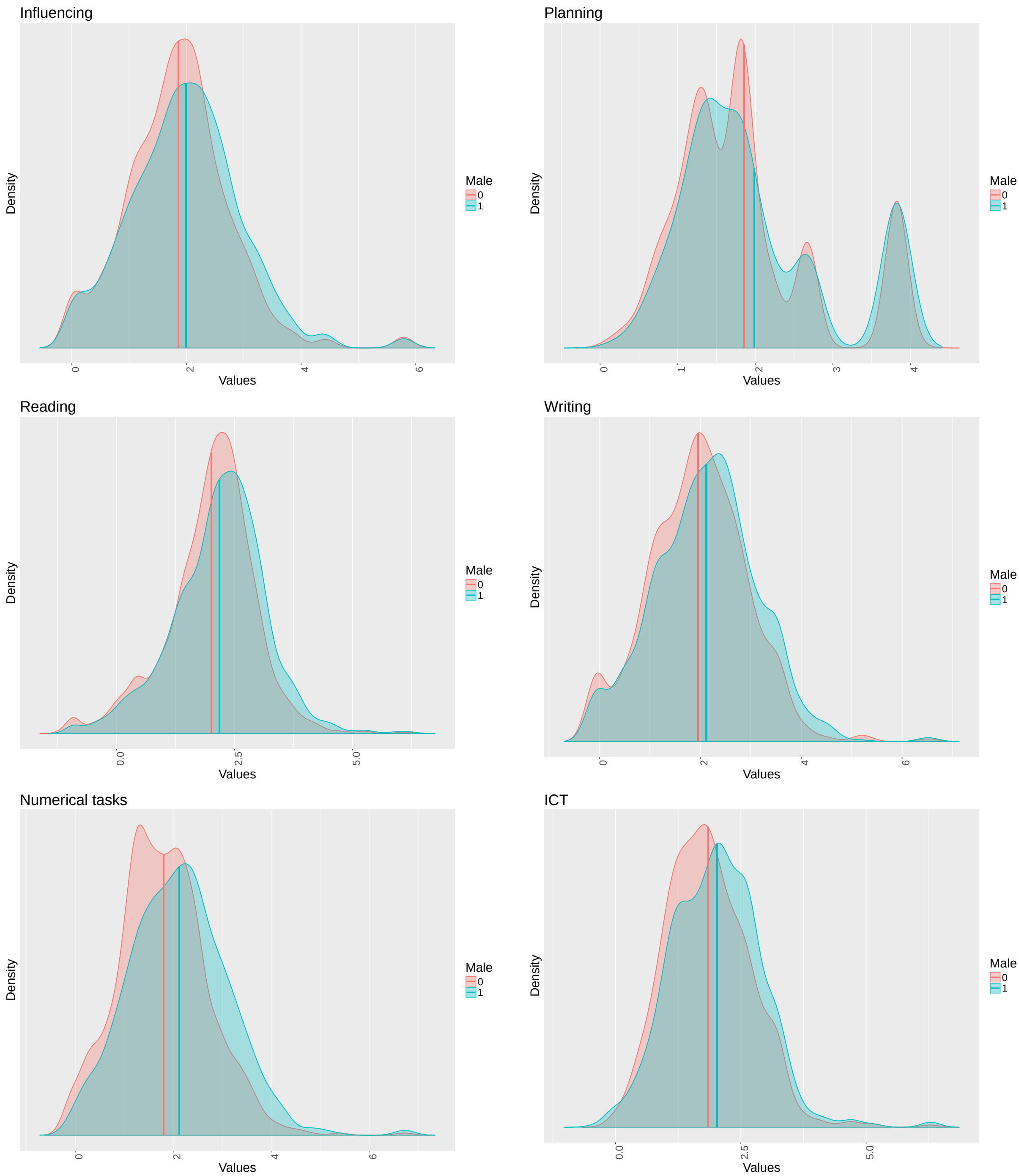


Figure 2: Tasks at work: gender differences in Austria

Skill Match. Thirdly, we can assess the matching of skills and job requirements. There are several skill match measures that can be used within the PIAAC data framework (see e.g. Allen et al. (2013), Desjardins et al. (2013) or Köppl-Turyna and Christl (2018)). The PIAAC data set includes a self-reported variable of skills utilization (that is specific to the Austrian edition of the PIAAC survey), which asks participants to assess the utilization of their skills and knowledge, with the answer varying between "not at all" and "to a very high extent". But the self assessment of skill match comes along with several drawbacks. A paper by Perry et al. (2016) compares several existing skill match variables and concludes that respondents substantially overestimate the skill mismatch (see e.g Hartog (2000)).

But skill mismatch can be measured directly. Perry et al. (2016) argue that this provides a more objective measure. In those direct skill mismatch measures approaches, workers skills are compared to skills required at their workplace. They show that compared to the self-assessed data, these skill measures indicate substantially lower numbers in over-skilled workers and slightly higher number in under-skilled workers.

Therefore, we use a method introduced by Allen et al. (2013) that standardizes skill scores and tasks (for both, numeracy and literacy skills separately) to make both measures comparable. Mismatch is further defined by a deviation of skills and skill use (tasks) by at least 1.5 standard deviations from the average. Using this mismatch indicator we can only see small gender differences in over-skilled and under-skilled workers, where men are slightly more likely to be under-skilled while women are slightly more likely to be over-skilled.

Job Flexibility. Fourthly, we try to take a closer look at job flexibility, which is not often used as an explanatory variable due to lack of data. In the PIAAC data set, however, we are provided with information about the flexibility of working hours, which is a good overall measure of job flexibility in our opinion. Participants are asked about extent to which they can choose or change working hours. The answer can again vary between "not at all" and "to a very high extent".

Skills and Tasks. Interestingly, although the standard Roy model (see, e.g., Roy 1951, Heckman and Honore 1990) predicts that workers systematically sort themselves into different occupations, the correlation between the measure of tasks and the measures of cognitive skills suggests that there is considerable variation (Table 2), which can be exploited in the empirical investigation.

Variables	Numeracy (skill)	Numeracy (task)	Literacy (skill)	Literacy (task)	Problem-solving
Numeracy (task)	0.262				
Literacy (skill)	0.860	0.240			
Literacy (task)	0.313	0.438	0.290		
Problem-solving	0.707	0.195	0.787	0.157	
ICT (task)	0.260	0.487	0.271	0.500	0.273

Table 2: Correlations between tasks and skills

Whether self-selection to occupations according to tasks is indeed happening, will be formally tested according to Equation 2, in the next Section.

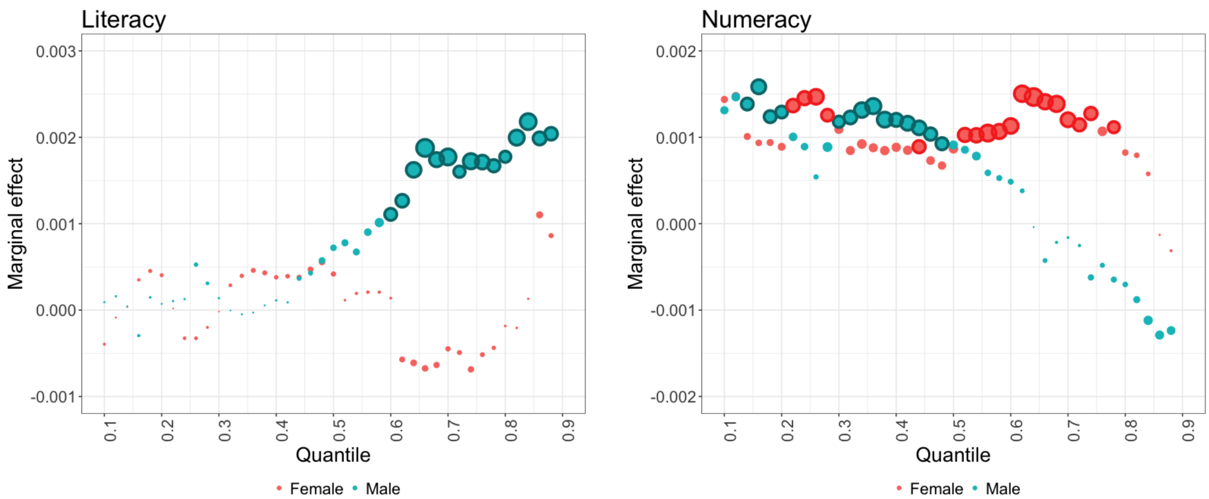
5. Results

In this section, we first provide an overview of the quantile regression results for men and women, and then determine the extent to which different characteristics influence the wages of both genders. Detailed results can be found in the Appendix, and the coefficients of interest are given in Figures 4, 5 and 6. In a second step, we take a closer look at how much of the unexplained part of the gender wage gap is influenced by skills and selection bias.

5.1. Wage Regressions: Gender-Specific Returns to Skills and Tasks

In this section, we focus on drivers that influence male and female wages. Quantile regression results for men and women are shown in Tables A.6, A.7, A.8 and A.9 in the Appendix. Typical variables, such as experience and education, show, as expected, a significant positive effect on wages. There seem to be no large differences between genders in the coefficients for typical explanatory variables such as experience and education. Additionally, the smaller the firm size, the lower the wage, which is consistent with some previous findings. We can see that small firms (one to 10 employees), in particular, pay significantly less than the largest companies.

With respect to differences in returns to cognitive skills, the results reported in Figure 3 confirm previous findings that higher numeracy and literacy skills are significantly positively related with high wages[6]. There are also visible differences between the two genders: while literacy skills are positively correlated with wages in the upper part of the income distribution for males, coefficients of wage regression for females are not significant. On the other hand, numeracy is positively associated with wages for females, for quantiles between 25% and 75% and for males below the median. 10 points increase on a 500 points scale means about 1% to 2% higher wage.



Remark: Coefficients scaled according to their t-statistics - larger circles denoting higher significance; dark-bordered circles denote significance at 95% level.

Figure 3: Wage regression coefficients for skills

The largest differences between men and women emerge when we take a closer look at tasks at work (Figure 4). As the overall effect of tasks combines the unconditional effect and the interaction term, the figure shows the marginal effects, that is accounts for the fact that workers may sort into diverse occupations. Our results indicate a wage premium for reading for women. The reading premium is about 2% to 6% across the wage distribution, and is highly significant. Premiums for writing and ICT tasks are less straightforward, yet, ICT tasks give females above the median income about 2% higher wage. Numerical tasks, for example, do not show positive effects at any conventional level, as opposed to the actual cognitive skills for females. This is in contrast to male-based tasks premiums, where numerical tasks (3% to 4%) and influencing tasks (between 2% and 4%), in particular, have a significant

[6]see also A.6 and A.8

influence on wages. ICT tasks correspond to about 2% to 3% increase in wages for males for quantiles 25% to 60%. On the other hand, planning tasks for males are related with lower wages, of about 2%.

Skill mismatch for literacy skills do not influence wages significantly, except in the top of the earnings distribution. But for numeracy skill mismatch, we can see substantial gender differences in returns to mismatch. Figure 5 shows that over-qualification lead to a significant wage premium for males for quantiles up to 75%, while there is a significant wage penalty for women for quantiles between 50% and 75%. In the literature, over-qualification is typically associated with wage penalties[7]. For under-qualification in numeracy, we can not see significant results.

Work flexibility shows opposite signs for women and men (Figure 6). While for males, flexible jobs are rewarded (no flexibility leads to a wage decrease of about 10%,across all income levels, compared to high flexibility), jobs for women that are less flexible pay more than those that offer flexible working hours (no flexibility increases the wage by almost 10% compared to high flexibility in the low-income part of the income distribution). This fact, taken together with the skill premiums, suggests that job flexibility for females has a different form to that for males. Women might typically work in jobs requiring office-based skills, such as reading and planning, which are not associated with flexible working hours. It seems that these types of occupations are generally less well rewarded than ICT and managerial positions, even when educational backgrounds are similar. This result is in line with Goldin (2014).

Having children seems to have a negative effect on wages for women, but only in the middle of the income distribution is this negative impact significant. In Austria, this is likely to be associated with age, as younger females experience lower wages resulting from career breaks, while those receiving wages at the very top of the distribution, due to seniority, will typically have adult children. On the other hand, there seems to be a child bonus for men, especially for low- and middle-income earners, although the coefficients are not significant.

[7]see e. g. Perry et al. (2016)

	(1) 10%	(2) 25%	(3) 50%	(4) 75%	(5) 90%
			Males		
Mean Influencing × Influencing	0.01	0.02*	0.01	-0.00	-0.00
	(0.66)	(1.94)	(0.85)	(-0.40)	(-0.01)
Mean Numerical × Numerical	-0.00	0.01	-0.00	0.01	-0.00
	(-0.19)	(0.52)	(-0.06)	(0.72)	(-0.28)
Mean Planning × Planning	0.03	0.01	0.02	0.03	0.00
	(1.15)	(0.62)	(1.22)	(1.42)	(0.18)
Mean Reading × Reading	0.04*	0.03**	0.03***	0.05***	0.01
	(1.68)	(2.34)	(2.75)	(3.56)	(0.66)
Writing × Mean Writing	0.01	0.01	-0.00	-0.02*	-0.04**
	(0.97)	(1.41)	(-0.30)	(-1.85)	(-2.28)
ICT × Mean ICT	-0.00	-0.01	-0.00	-0.01	-0.00
	(-0.04)	(-0.67)	(-0.38)	(-1.08)	(-0.11)
			Females		
Mean Influencing × Influencing	0.02	0.02	0.02**	0.03	0.01
	(0.60)	(1.36)	(2.01)	(1.63)	(0.35)
Mean Numerical × Numerical	0.01	0.00	0.00	-0.03	-0.04
	(0.41)	(0.17)	(0.21)	(-1.51)	(-1.60)
Mean Planning × Planning	0.03	-0.01	-0.03**	-0.03	-0.01
	(0.66)	(-0.44)	(-2.15)	(-1.31)	(-0.32)
Mean Reading × Reading	-0.01	0.02	0.01	0.01	0.04*
	(-0.22)	(1.41)	(1.04)	(0.41)	(1.84)
Writing × Mean Writing	-0.01	-0.02	-0.01	-0.02	-0.02
	(-0.43)	(-1.12)	(-0.44)	(-1.42)	(-1.14)
ICT × Mean ICT	-0.00	-0.00	-0.00	0.02	0.01
	(-0.06)	(-0.02)	(-0.07)	(1.12)	(0.50)

In all regressions, the unconditional effects of individual- and occupation-level tasks, as well as the full set of control variables as in Table A.5 included.
Significance * 0.1, ** 0.05, *** 0.01, t-statistics in brackets.

Table 3: Testing comparative advantages - quantile regressions of (log) hourly wage on the interactions between individual and occupation-level tasks

5.1.1. Testing self-selection to occupations

Table 3 presents the interaction terms between the individual and occupation-level tasks variables, for several quantiles of the wage distribution. The mean values for each task group are calculated across the ISCO occupation codes.

The general picture emerges: in most cases, we do not observe any evidence consistent with sorting. Most of the coefficients listed in Table 3 are not significant at any conventional level. One exception emerges, however. For the case of males and quantiles between 10% and 75%, the interaction term between the occupation- and individual-level reading task variable is positive and significant, suggesting the comparative advantage hypothesis. At the same time, interaction-terms for females are insignificant. This result means that only do females and males posses different skills, but that the mechanism of self-selection into occupations according to the reading tasks between the genders could be different, or only present for the case of male workers.

5.2. Effects of Gender-Specific Skills and Tasks on the Gender Wage Gap

As a benchmark case, we first estimate the gender gap using a similar set of control variables as Böheim et al. (2013a), without any additional control for individual skills, to ensure that the findings derived from the new data set can be compared to previous studies. Subsequently, we show how the estimation results change when we consider skills, tasks and skill matching. Finally, in the sample-selection model, we include personal characteristics affecting the decision to work as a result of the reservation wage, as well as characteristics that potentially affect wages, such as childcare, educational level, age and migration status. For the sample-selection model, we use the whole sample of 4,700 observations, which includes observations without wage information, e.g., for participants who are not working.

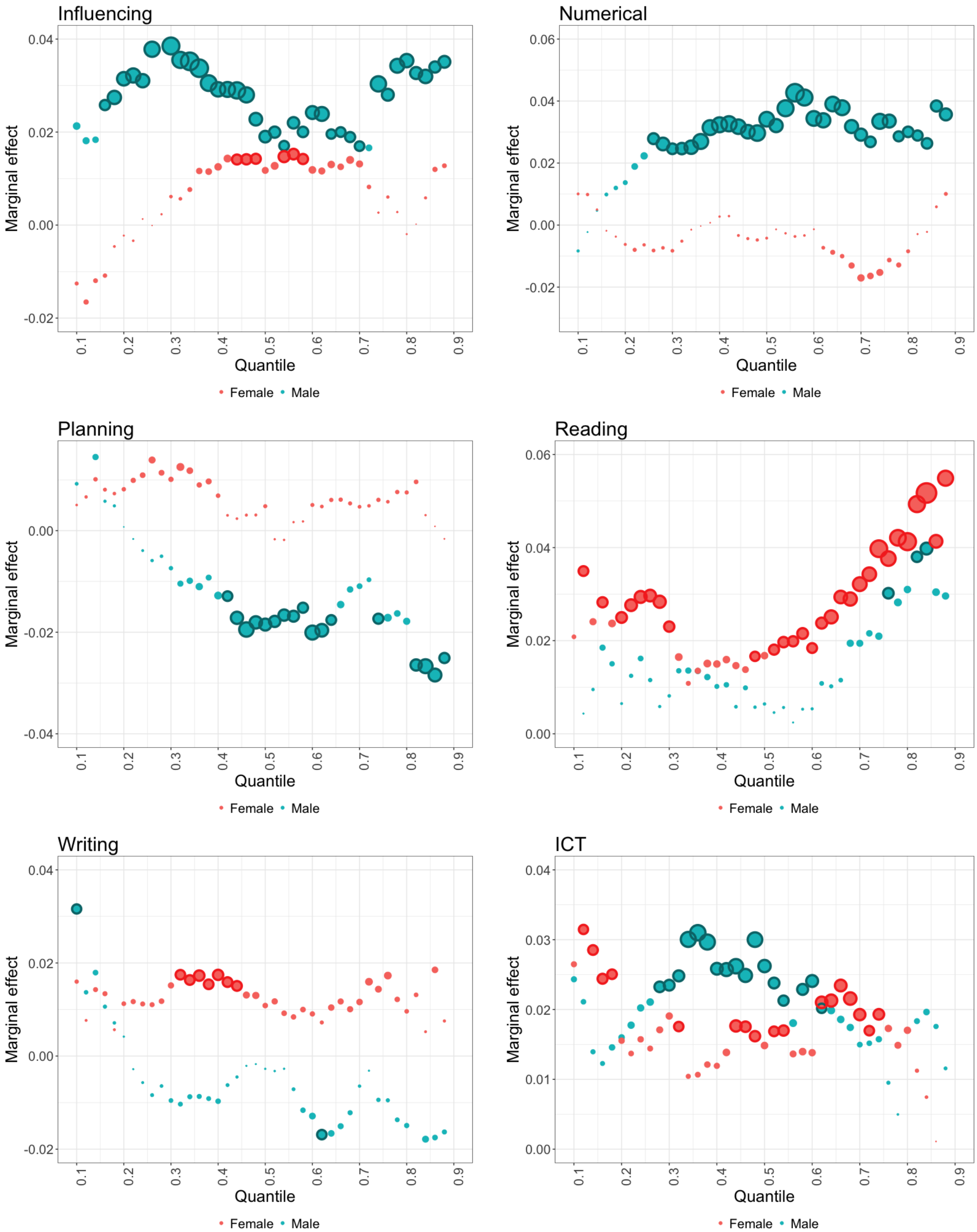
Benchmark Model of the Gender Wage Gap. In the first section, we compare the results of our study with previous specifications, in order to determine whether, when using the same set of controls, the wage differences have changed since Böheim et al. (2013a) published a study using data from 2007. We report decomposition results from male-based estimations[8].

The total gender wage gap in our data set ranges from 15% in the lower part of the income distribution up to almost 24 percent in the upper part.

Böheim et al. (2013a) showed that the unexplained gender wage gap was, on average, 13%. Using a similar model as a benchmark, our data suggest an unexplained gender wage gap between 8% and 19% across the wage distribution. In the middle of the wage distribution, our data reveal a unexplained gap of approximately 14%, indicating a similar gender wage gap to the previous studies in Austria.

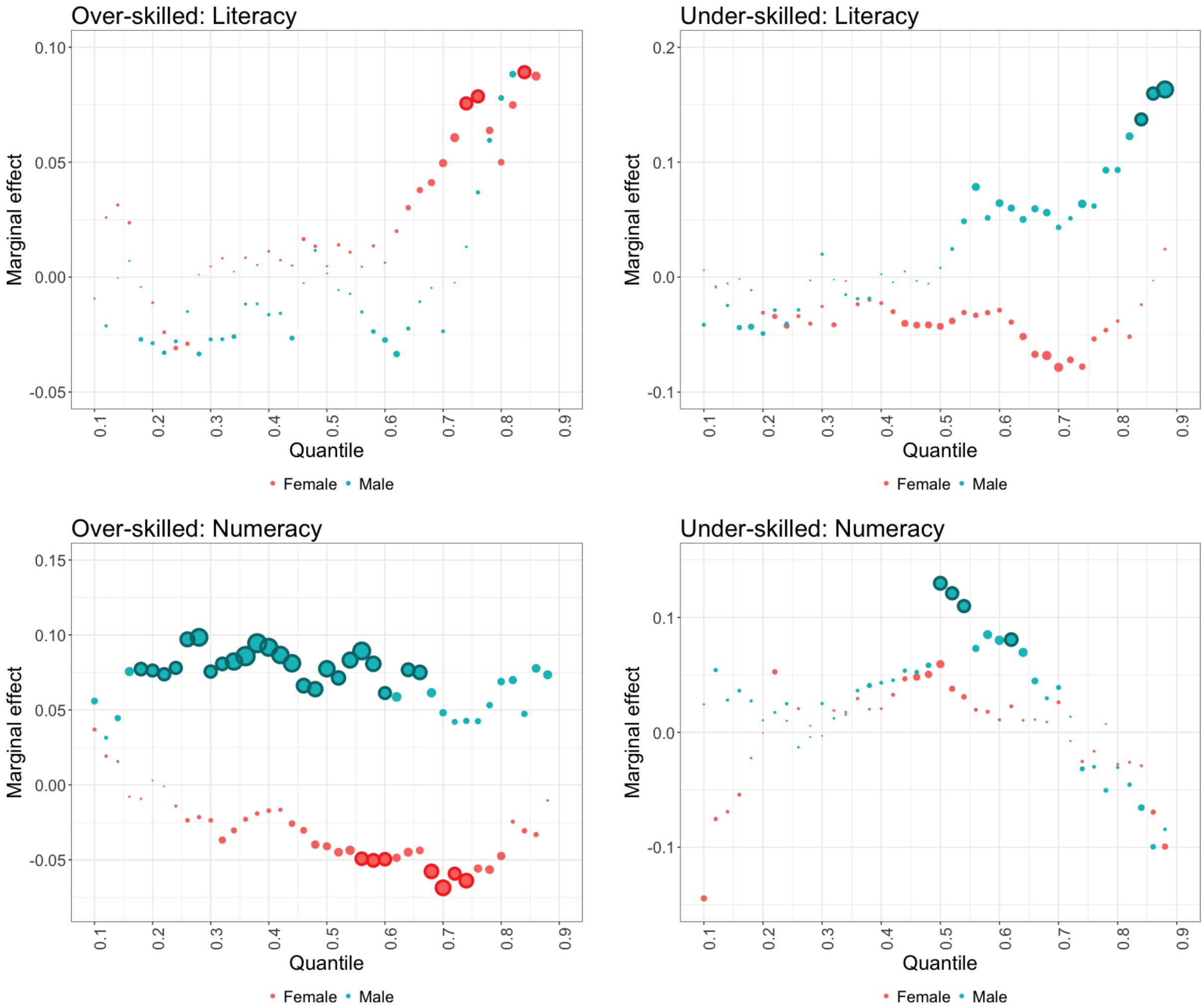
Our decomposition reveals that only about 3 to 6 percentage points of the gender wage gap can be explained in our dataset when we use typically used explanatory variables of the literature.

[8]We do not report any female-based results due to space constraints. Full results, however, can be obtained on request and are broadly consistent with the findings of Böheim et al. (2013a) and other studies, i.e., they show higher unexplained gender gaps than male-based results.



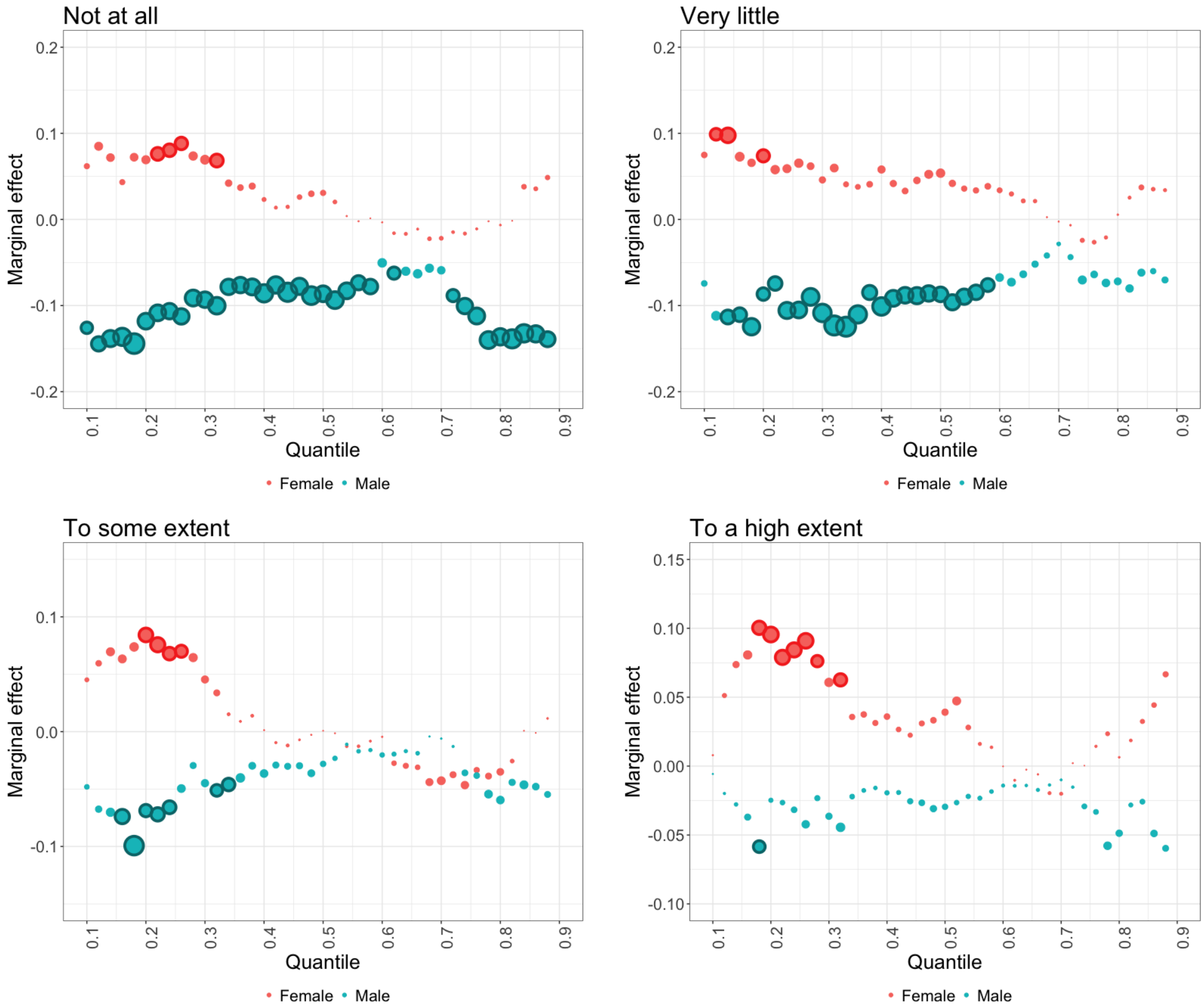
Remark: Coefficients scaled according to their t-statistics - larger circles denoting higher significance; dark-bordered circles denote significance at 95% level.

Figure 4: Average marginal effects of tasks



Remark: Coefficients scaled according to their t-statistics - larger circles denoting higher significance; dark-bordered circles denote significance at 95% level.

Figure 5: Wage regression coefficients for over- and under-skilled (base level: correctly skilled)



Remark: Coefficients scaled according to their t-statistics - larger circles denoting higher significance; dark-bordered circles denote significance at 95% level.

Figure 6: Wage regression coefficients for job flexibility (base level = "to a very high extent")

	benchmark				new model			
quantile	total difference	explained	explained fraction	unexplained	adjusted total difference	explained	explained fraction	unexplained
1	14.85	6.40	43%	8.45	10.62	9.41	89%	1.22
2	15.82	5.22	33%	10.60	12.94	11.03	85%	1.92
3	16.52	4.26	26%	12.25	15.86	12.69	80%	3.17
4	16.56	3.32	20%	13.24	17.88	13.33	75%	4.55
5	16.80	2.65	16%	14.15	19.64	13.96	71%	5.67
6	17.63	2.92	17%	14.71	22.36	14.55	65%	7.82
7	18.64	2.85	15%	15.78	23.97	15.51	65%	8.47
8	20.26	3.87	19%	16.39	26.25	15.83	60%	10.42
9	23.73	4.66	20%	19.07	27.98	16.39	59%	11.59

Table 4: Effects of coefficients (male-based)

The low level of the unexplained gender wage gap at the lower tail of the distribution is consistent with the fact that low-income earners in Austria are usually covered by collective bargaining rules. These laws are gender-neutral and do not allow for discrimination. Therefore, while the result is not surprising, as mentioned above, it could indicate that choosing whether to work is a factor (to be discussed later). The unexplained part of the gender wage gap increases along the wage distribution when we move from collective to individual bargaining.

Results Including Skills, Tasks and Skill Matching and correction for sample selection. The Austrian gender wage gap literature so far misses two crucial points of the discussed topics. First, non-observed characteristics that might differ for males and females and that are typically not covered in traditional datasets, such as skills of worker, the exact tasks that are performed in a job and whether the skills and the tasks of the workers are well matched. As we have seen before, not only the returns to those characteristics differ between gender, but also the endowment. Therefore adding those characteristics to the wage decomposition might help to explain more of the gender wage gap- or might even increase the non-explanatory part.

Second, the Austrian literature does not control for sample selection. If, for instance, the reservation wage of a woman depends on her productivity, and potentially, therefore, the same factors as the observed wages, the estimates will be biased due to the sample selection. In essence, failure to correct for the sample selection means comparing the wages of a representative sample of males with a censored sample of females, where the censoring implies that the least-productive females are not observed. We additionally try to overcome with our new estimation methods. Details can be seen in the next paragraph.

First of all, we can see that the total gender wage gap is increasing, when we control for sample selection. While the range of the total gender wage gap was between 15% and 24%, it decreases substantially in the lower part but increases in the middle and upper part of the wage distribution. This seems to be on a first glance counter-intuitive. This might be driven by the fact, that women that earn low wage do not stay out of the workforce for childcare reasons, while this typically happens for women that earn better. An additional fact that

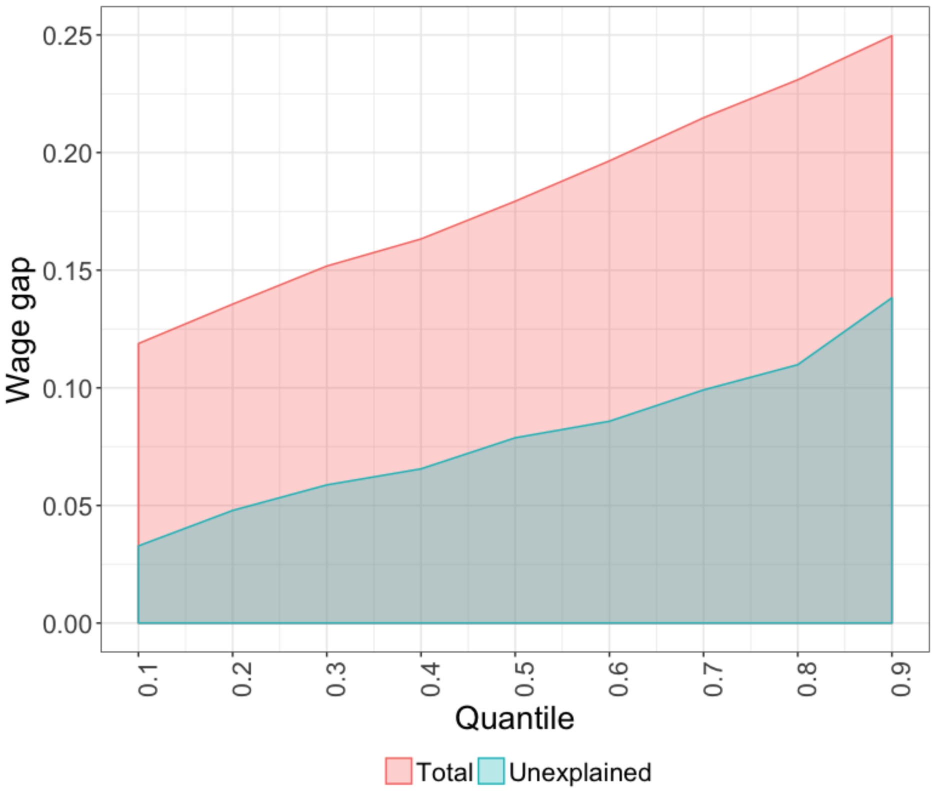


Figure 7: Wage differences when considering skills, tasks, skill matching and sample selcection

helps to explain this finding is that women tend to have children later in their life. Within the strong collective bargaining system with typically substantial seniority wages, women with children are less likely to be at lower end of the income distribution.

We can see that, especially all along the income distribution, the unexplained part of the gender wage gap is much less than in the benchmark model (see Table 4), indicating that skills, tasks and skill matching differ to a great extent between men and women and that sample selection plays a crucial role.

Compared to the 14.15% at the median for the benchmark case, the unexplained part reduces by almost nine percentage points to 5.67% in the new model, which confirms the significant influence of skills, tasks and skill matching on wage differences between men and women. At the upper part of the income distribution, we can still explain almost 60% of the gender wage gap, leaving an unexplained wage gap of 11.6%.

At the lower part of the income distribution, we can see that our model explains almost 90% of the gender wage gap. Within a strong collective bargaining framework as in Austria, where more than 95% of the workers are covered by collective bargaining this seems not surprising.

While different returns to task for females and males can be observed in our analysis, we can not see any influence on the unexplained (coefficient-related) part in the gender wage gap analysis. This result indicates that higher returns for males for e.g. numerical tasks and others cancel out with lower returns for reading and writing tasks. On the other hand, the explained (endowment-related) part of the gender wage gap increases when we add the task variables in the specification indicating that the endowment effect is highly relevant in explaining the gender wage gap, while the unexplained (coefficient-related) part is overall not influenced by the differences in returns to specific tasks.

Figure 8 shows the results of decomposition across the wage distribution when we correct for sample selection and add the skill and task variables. Especially in the lower part of the distribution, we can see a substantial decrease in the unexplained part of the gender wage gap (red surface), compared to the results without of the benchmark model.

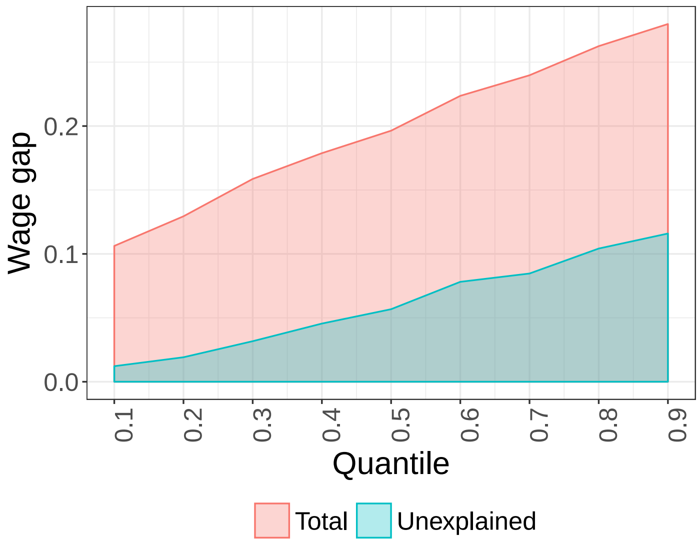


Figure 8: Wage differences with sample selection

Sample Selection Correction. In Table **??** in the Appendix, we report the results of the selection equation where the dependent variable is a dummy for working. Table **??** presents the results of a probit regression, which is subsequently used to perform the Arellano and Bonhomme (2017) estimation.

We observe that the replacement rate of an individual is a significant predictor of being employed. The probability of working is reduced with an increase in the net replacement rate for both genders, although the effect on females seems to be more pronounced. Age is an additional statistically significant predictor for the decision to work. The older people are, the more likely it is that they work. The same holds true for the privacy status. Females that live with a partner have a higher probability of working.

As for the variables that involve both the selection and the wage equation, the level of education has a significant impact on the work decision for women, in line with our predictions. Better-educated women have a higher probability of working, compared to individuals with a lower level of education. Additionally, migrant women tend to have a lower probability of working.

6. Summary and Conclusions

Our paper analyzes the gender differences in skills and tasks of workers and their impact on the gender wage gap for Austria across the wage distribution. We use a quantile regression approach and combine it with a decomposition method following Chernozhukov et al. (2013). Additionally, we account for the self-selection problem in accordance with Arellano and Bonhomme (2017).

Our results are in line with Böheim et al. (2013b), who showed that the unexplained wage gap in Austria was approximately 13% in 2007. When we use our data with a similar specification, the results remain fairly close to this result for 2011. However, a new feature of this work is the use of data from the PIAAC survey conducted by the OECD in 2011/12. This allows us to control for skills, tasks, skill matching and work flexibility, which are often considered to affect wages even within the same occupations.

Adding these variables to the wage regressions for males and females reveals some interesting insights. When we take a closer look at female skill use, we can see that there is a wage premium for planning skills, reading skills and writing skills. This is in stark contrast to the male-based skill premium, where influencing, numerical skills and ICT skills have a positive influence on wages. Meanwhile, skill matching has a positive influence on wages for both genders. On the other hand, flexibility at work is rewarded for males, but has a negative premium for females.

When we add the skill and task variables to our model and control for sample selection, the unexplained part of the gender wage gap decreases by about six to nine percentage points across the entire wage distribution. Our results show that in the lower part of the wage distribution, the unexplained gender wage gap is less than 2%. When we move across the wage distribution, the unexplained gender wage gap increases to a maximum of about 12% at the upper end of the distribution. This highlights the importance of accounting for additional individual characteristics (skills) and task profiles, when analyzing differences in wages between males and females.

The low unexplained part of the gender wage gap in the lower part of the income distribution is mostly due to the fact that most employees are covered by collective minimum wages and collective bargaining; factors which do not allow for gender discrimination. When we move further across the wage distribution, bargaining changes from collective to individual bargaining. It therefore seems that individual bargaining has a substantial impact on the differences in wages between men and women. As we show, this also appears to hold true for bonus payments. Whether this is due to differences in individual bargaining behavior, missing characteristics (such as complex job (task) profiles at the upper part of the distribution) or purely to discrimination, cannot be determined by our methodology.

Controlling for sample selection is an important issue to address for determining the size of the gender wage gap. Our results show that the total gender wage gap decreases in the lower part of the distribution, while it increases after the 3rd decile. A reason might be, that women that earn low wage do not stay out of the workforce for childcare reasons due to financial constraints. An additional fact that helps to explain this finding is that women tend to have children later in their life. Within the strong collective bargaining system with typically substantial seniority wages, women with children are less likely to be at lower end of the income distribution.

Several authors, when analyzing the gender wage gap, conclude that the unexplained part is decreasing over time. However, our findings that additional information on the job and worker characteristics (such as skills, tasks and skill matching) reduce the unexplained gender wage gap, rather suggest that part of the decrease over time can be attributed to better data access and more sophisticated econometric techniques. This in turn implies that a consistent estimation of the gender wage gap over time is still missing, while clear-cut evidence for a decreasing gender wage gap is yet to be presented. However, there are indications that the gap seems to be much narrower than hypothesized. This means that we could be closer to explaining the gender wage gap than we initially thought, especially with regard to low-income earners.

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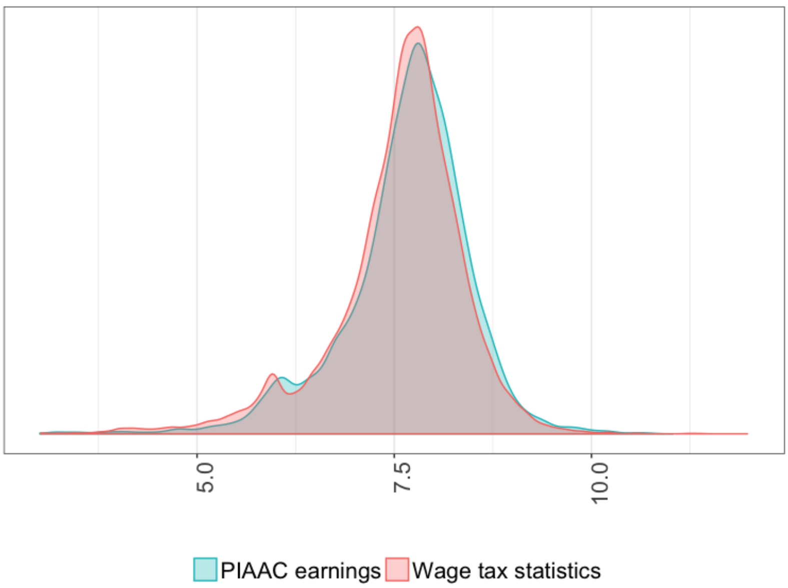
Appendix A. Additional Tables and Figures

Figure A.9: Log hourly wages without bonus payments: all workers (left panel), full-time workers (right panel)



Comment: We adjust the wage statistics for 2012 for persons below the age of 65 by including only taxpayers who were employed during the whole year and dividing by 14 months to calculate valid monthly wages comparable to PIAAC monthly wages. For the PIAAC data 2011/2012, we leave out the self-employed, who are not included in the tax statistics.

Figure A.10: Wage distribution - PIAAC vs. wage statistics

Type	Variable	Categories
Personal characteristics	Education level	ISCED 2011 classification code dummy
	Relevant job experience	in years
	Children	number of
	Age of youngest child	four categories of age
	Out of workforce due to childcare	dummy for previous career breaks due to childcare obligations
	Migration background	migrant (1st or 2nd generation)
Job characteristics	Employment status	dummy for blue-collar, white-collar, public servant and contracted public employee
	Firm size	1 to 10, 11 to 50, 51 to 250, 251 to 1000 and ¿1000 employees
	Participation in on-the-job training	dummy
	Hours worked per week	between 1 and 60 hours per week
	Economic sector	dummy NACE (2-digit) sector
	Type of activity	dummy ISCO (2-digit) activity classification
	Work flexibility	none, little, moderate, high, very high
Skill use	ICT skills	measured in PIAAC: five categories of skill use
	Influencing skills	measured in PIAAC: five categories of skill use
	Numeracy skills	measured in PIAAC: five categories of skill use
	Planning skills	measured in PIAAC: five categories of skill use
	Writing skills	measured in PIAAC: five categories of skill use
	Reading skills	measured in PIAAC: five categories of skill use
Cognitive skills	assessed scores	measured in PIAAC
	Literacy	0 to 500 points
	Numeracy	0 to 500 points
Skill match		”To what extent can you use your knowledge and skills at your current work?” between ”not at all” and ”to a very high extent”

Table A.5: Overview of the independent variables

	(1) 10%	(2) 25%	(3) 50%	(4) 75%	(5) 90%
			Cognitive skills		
Literacy	-0.00	0.00	0.00	0.00**	0.00**
	(-0.03)	(0.38)	(1.46)	(2.20)	(2.42)
Numeracy	0.00**	0.00	0.00*	-0.00	-0.00*
	(2.04)	(1.06)	(1.78)	(-0.61)	(-1.66)
Over-skilled: Literacy	-0.01	-0.03	0.01	0.02	0.16***
	(-0.17)	(-0.58)	(0.24)	(0.37)	(2.82)
Under-skilled: Literacy	-0.04	-0.04	0.01	0.05	0.14**
	(-0.65)	(-0.72)	(0.12)	(0.92)	(2.00)
Over-skilled: Numeracy	0.06	0.10***	0.08***	0.05	0.05
	(1.45)	(2.83)	(2.78)	(1.53)	(0.99)
Under-skilled: Numeracy	0.02	-0.01	0.11**	-0.03	-0.07
	(0.14)	(-0.18)	(1.99)	(-0.57)	(-0.47)
			Tasks		
Mean Influencing	-0.20	-0.28***	-0.11**	-0.10	-0.30**
	(-1.63)	(-3.56)	(-2.06)	(-0.98)	(-2.27)
Influencing	-0.01	-0.03	-0.01	0.04	0.03
	(-0.27)	(-0.90)	(-0.23)	(1.53)	(0.74)
Mean Influencing × Influencing	0.01	0.02*	0.01	-0.00	-0.00
	(0.66)	(1.94)	(0.85)	(-0.40)	(-0.01)
Mean Numerical	0.19**	0.07	0.07	-0.13*	-0.33**
	(2.02)	(1.01)	(1.19)	(-1.73)	(-2.52)
Numerical	0.00	0.01	0.04	0.01	0.04
	(0.04)	(0.32)	(1.39)	(0.39)	(0.82)
Mean Numerical × Numerical	-0.00	0.01	-0.00	0.01	-0.00
	(-0.19)	(0.52)	(-0.06)	(0.72)	(-0.28)
Mean Planning	-0.12	0.08	0.14	0.50**	1.25***
	(-0.61)	(0.55)	(1.17)	(2.24)	(4.55)
Planning	-0.06	-0.03	-0.06*	-0.09*	-0.04
	(-1.00)	(-0.74)	(-1.74)	(-1.81)	(-0.58)
Mean Planning × Planning	0.03	0.01	0.02	0.03	0.00
	(1.15)	(0.62)	(1.22)	(1.42)	(0.18)
Mean Reading	0.14	0.25*	0.06	-0.01	0.24
	(0.68)	(1.80)	(0.54)	(-0.05)	(1.05)
Reading	-0.12*	-0.10**	-0.10***	-0.15***	-0.01
	(-1.92)	(-2.20)	(-2.73)	(-3.15)	(-0.16)
Mean Reading × Reading	0.04*	0.03**	0.03***	0.05***	0.01
	(1.68)	(2.34)	(2.75)	(3.56)	(0.66)
Writing	-0.01	-0.05	0.01	0.06*	0.09**
	(-0.21)	(-1.57)	(0.22)	(1.81)	(1.97)
Mean Writing	-0.23*	-0.17*	-0.04	0.02	-0.01
	(-1.67)	(-1.92)	(-0.59)	(0.25)	(-0.12)
Writing × Mean Writing	0.01	0.01	-0.00	-0.02*	-0.04**
	(0.97)	(1.41)	(-0.30)	(-1.85)	(-2.28)
ICT	0.03	0.04	0.04	0.04	0.02
	(0.65)	(1.23)	(1.30)	(1.41)	(0.28)
Mean ICT	-0.05	-0.14*	-0.18***	-0.21**	-0.31*
	(-0.35)	(-1.78)	(-3.08)	(-2.20)	(-1.74)
ICT × Mean ICT	-0.00	-0.01	-0.00	-0.01	-0.00
	(-0.04)	(-0.67)	(-0.38)	(-1.08)	(-0.11)
			Work flexibility		
Not at all	-0.12**	-0.10***	-0.09***	-0.11***	-0.11**
	(-2.05)	(-3.12)	(-3.34)	(-3.19)	(-2.47)
Very little	-0.07	-0.09***	-0.09***	-0.07	-0.08*
	(-1.27)	(-2.73)	(-3.02)	(-1.64)	(-1.85)
To some extent	-0.04	-0.03	-0.03	-0.04	-0.06
	(-0.93)	(-1.25)	(-1.21)	(-1.36)	(-1.47)
To a high extent	-0.01	-0.03	-0.02	-0.04	-0.04
	(-0.11)	(-1.18)	(-0.92)	(-1.12)	(-1.04)
To a very high extent				base	
			Education		
ISCED 1+2				base	
ISCED 3	0.01	0.07	0.09**	0.12***	0.22***
	(0.19)	(1.20)	(2.07)	(3.48)	(3.20)
ISCED 4	0.17**	0.17***	0.19***	0.23***	0.33***
	(2.06)	(2.99)	(3.83)	(5.51)	(4.10)
ISCED 5+6	0.17*	0.21***	0.28***	0.31***	0.41***
	(1.96)	(3.73)	(5.73)	(7.06)	(5.68)
Experience	0.05***	0.04***	0.03***	0.03***	0.03***
	(9.97)	(9.30)	(9.53)	(7.88)	(4.89)
Experience ^{2}	-0.00***	-0.00***	-0.00***	-0.00***	-0.00**
	(-6.16)	(-6.40)	(-5.42)	(-4.51)	(-2.07)
			On-the-job training		
Yes	0.08***	0.02	-0.00	-0.02	-0.02
	(3.03)	(0.92)	(-0.22)	(-1.14)	(-0.62)
Public Sector	-0.03	0.08*	0.07**	-0.02	-0.05
	(-0.54)	(1.94)	(2.00)	(-0.34)	(-0.63)

Industry (NACE-1) classifications included in all regressions; observations weighted with PIAAC post-stratification weights
Significance * 0.1, ** 0.05, *** 0.01, t-statistics in brackets.

Table A.6: Quantile regressions with skills - hourly wages - results for males

	(1) 10%	(2) 25%	(3) 50%	(4) 75%	(5) 90%
			Job status		
White-collar	0.17**	0.16**	0.16***	0.11**	0.13
	(2.58)	(2.26)	(3.82)	(2.53)	(1.64)
Blue-collar	0.04	0.05	0.08*	0.03	0.10
	(0.62)	(0.70)	(1.76)	(0.58)	(1.22)
Civil servant	0.18***	0.15**	0.14***	0.14***	0.09
	(2.77)	(2.21)	(3.63)	(3.49)	(1.22)
Contracted public servant				base	
			Firm size		
one to 10	-0.19***	-0.19***	-0.19***	-0.21***	-0.20***
	(-2.79)	(-3.93)	(-6.18)	(-3.78)	(-3.24)
11 to 50	0.04	-0.07	-0.12***	-0.18***	-0.23***
	(0.61)	(-1.45)	(-4.45)	(-3.74)	(-4.34)
51 to 250	0.08	-0.02	-0.11***	-0.12**	-0.18***
	(1.38)	(-0.49)	(-3.95)	(-2.44)	(-3.35)
251 to 1000	0.15***	-0.00	-0.01	-0.04	-0.06
	(2.80)	(-0.06)	(-0.52)	(-0.72)	(-1.01)
more than 1,000 people				base	
			Children		
Children	-0.05*	-0.04*	0.01	0.07**	-0.01
	(-1.86)	(-1.79)	(0.30)	(2.50)	(-0.33)
Aged 2 or younger	0.04	0.04	0.00	-0.08**	-0.05
	(0.87)	(1.08)	(0.18)	(-2.36)	(-0.76)
Aged 3-5	-0.07	0.11	0.06	-0.03	-0.00
	(-1.01)	(0.93)	(1.15)	(-0.56)	(-0.04)
Aged 6-12	-0.05	0.06	0.05	-0.04	-0.09
	(-0.65)	(0.63)	(1.31)	(-0.84)	(-1.07)
Migrant	0.05	-0.01	-0.03*	-0.06*	0.03
	(1.23)	(-0.36)	(-1.67)	(-1.83)	(0.55)
Hours Worked	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-4.00)	(-3.93)	(-5.59)	(-4.49)	(-4.21)

Industry (NACE-1) classifications included in all regressions; observations weighted with PIAAC post-stratification weights
Significance * 0.1, ** 0.05, *** 0.01, t-statistics in brackets.

Table A.7: Quantile regressions with skills - hourly wages - results for males cont'd

	(1) 10%	(2) 25%	(3) 50%	(4) 75%	(5) 90%
			Cognitive skills		
Literacy	-0.00	-0.00	0.00	-0.00	0.00
	(-0.42)	(-0.43)	(0.71)	(-0.94)	(0.64)
Numeracy	0.00	0.00**	0.00**	0.00**	-0.00
	(1.35)	(2.26)	(2.02)	(2.17)	(-0.52)
Over-skilled: Literacy	-0.03	-0.03	0.02	0.08**	0.15***
	(-0.35)	(-0.85)	(0.54)	(2.12)	(2.78)
Under-skilled: Literacy	0.01	-0.04	-0.03	-0.06	0.02
	(0.10)	(-0.89)	(-1.25)	(-1.00)	(0.25)
Over-skilled: Numeracy	0.03	-0.02	-0.04*	-0.06*	0.01
	(0.43)	(-0.74)	(-1.72)	(-1.90)	(0.12)
Under-skilled: Numeracy	-0.16	0.01	0.04	-0.03	-0.13
	(-1.02)	(0.12)	(0.90)	(-0.45)	(-1.44)
			Tasks		
Mean Influencing	-0.15	-0.16	0.03	-0.04	0.04
	(-0.24)	(-0.95)	(0.29)	(-0.25)	(0.11)
Influencing	-0.07	-0.07	-0.04	-0.07*	-0.01
	(-0.73)	(-1.34)	(-1.55)	(-1.65)	(-0.16)
Mean Influencing × Influencing	0.02	0.02	0.02**	0.03	0.01
	(0.60)	(1.36)	(2.01)	(1.63)	(0.35)
Mean Numerical	-0.42	-0.01	-0.03	-0.05	-0.02
	(-1.05)	(-0.05)	(-0.28)	(-0.44)	(-0.09)
Numerical	-0.02	-0.01	-0.01	0.06	0.12
	(-0.26)	(-0.29)	(-0.26)	(1.17)	(1.58)
Mean Numerical × Numerical	0.01	0.00	0.00	-0.03	-0.04
	(0.41)	(0.17)	(0.21)	(-1.51)	(-1.60)
Mean Planning	0.22	0.02	0.02	0.36	0.50
	(0.24)	(0.05)	(0.13)	(1.54)	(0.78)
Planning	-0.07	0.04	0.08**	0.08	0.02
	(-0.60)	(0.64)	(2.16)	(1.47)	(0.25)
Mean Planning × Planning	0.03	-0.01	-0.03**	-0.03	-0.01
	(0.66)	(-0.44)	(-2.15)	(-1.31)	(-0.32)
Mean Reading	0.22	0.23	-0.02	0.08	-0.10
	(0.30)	(1.00)	(-0.17)	(0.35)	(-0.22)
Reading	0.04	-0.05	-0.03	0.02	-0.06
	(0.40)	(-0.82)	(-0.64)	(0.34)	(-0.93)
Mean Reading × Reading	-0.01	0.02	0.01	0.01	0.04*
	(-0.22)	(1.41)	(1.04)	(0.41)	(1.84)
Writing	0.04	0.06	0.03	0.07*	0.06
	(0.51)	(1.30)	(0.77)	(1.80)	(1.32)
Mean Writing	0.20	0.00	0.15*	0.07	0.07
	(0.61)	(0.03)	(1.83)	(0.65)	(0.33)
Writing × Mean Writing	-0.01	-0.02	-0.01	-0.02	-0.02
	(-0.43)	(-1.12)	(-0.44)	(-1.42)	(-1.14)
ICT	0.03	0.01	0.02	-0.02	-0.02
	(0.34)	(0.25)	(0.46)	(-0.54)	(-0.35)
Mean ICT	-0.09	-0.11	-0.06	-0.17	-0.20
	(-0.12)	(-0.63)	(-0.50)	(-1.11)	(-0.45)
ICT × Mean ICT	-0.00	-0.00	-0.00	0.02	0.01
	(-0.06)	(-0.02)	(-0.07)	(1.12)	(0.50)
			Work flexibility		
Not at all	0.07	0.09**	0.03	-0.02	0.05
	(1.39)	(2.43)	(1.05)	(-0.61)	(1.30)
Very little	0.07	0.06*	0.05*	-0.03	0.02
	(1.26)	(1.84)	(1.78)	(-0.97)	(0.45)
To some extent	0.04	0.07***	0.00	-0.04	0.01
	(0.82)	(2.64)	(0.13)	(-1.36)	(0.20)
To a high extent	-0.00	0.09***	0.04	0.00	0.09*
	(-0.02)	(3.14)	(1.53)	(0.16)	(1.93)
To a very high extent				base	
			Education		
ISCED 1+2				base	
ISCED 3	0.12*	0.07	0.02	0.06*	0.09
	(1.83)	(1.07)	(0.58)	(1.87)	(1.18)
ISCED 4	0.22***	0.15**	0.06**	0.09**	0.09
	(2.76)	(2.10)	(2.02)	(2.42)	(1.11)
ISCED 5+6	0.31***	0.26***	0.23***	0.27***	0.30***
	(3.41)	(3.54)	(6.21)	(5.66)	(3.80)
Experience	0.04***	0.04***	0.02***	0.02***	0.02***
	(6.00)	(8.63)	(7.58)	(4.65)	(5.11)
Experience ^{2}	-0.00***	-0.00***	-0.00***	-0.00	-0.00*
	(-4.41)	(-5.82)	(-3.65)	(-1.15)	(-1.92)
			On-the-job training		
Yes	0.06*	0.01	-0.00	-0.04**	-0.04*
	(1.75)	(0.34)	(-0.27)	(-2.25)	(-1.84)
Public sector	0.04	0.01	0.06**	0.05	-0.01
	(0.41)	(0.24)	(2.53)	(1.60)	(-0.10)

Industry (NACE-1) classifications included in all regressions; observations weighted with PIAAC post-stratification weights
Significance * 0.1, ** 0.05, *** 0.01, t-statistics in brackets.

Table A.8: Quantile regressions with skills - hourly wages - results for females

	(1) 10%	(2) 25%	(3) 50%	(4) 75%	(5) 90%
			Job status		
White-collar	0.06	0.07	0.12***	0.07*	-0.03
	(0.91)	(1.45)	(3.59)	(1.86)	(-0.59)
Blue-collar	-0.01	0.05	0.09	0.02	-0.05
	(-0.05)	(0.62)	(1.53)	(0.33)	(-0.40)
Civil servant	0.19***	0.18***	0.12***	0.08	0.01
	(2.62)	(3.92)	(3.51)	(1.57)	(0.19)
Contracted public servant				base	
			Firm size		
one to 10	-0.21**	-0.15***	-0.11***	-0.04	-0.15**
	(-2.53)	(-3.07)	(-3.79)	(-0.64)	(-2.12)
11 to 50	-0.08	-0.06	-0.02	0.01	-0.07
	(-1.12)	(-1.49)	(-0.84)	(0.22)	(-1.11)
51 to 250	-0.10	-0.08*	-0.04	0.05	-0.03
	(-1.38)	(-1.84)	(-1.57)	(0.97)	(-0.39)
251 to 1000	-0.00	0.05	0.04	0.11**	-0.01
	(-0.04)	(1.01)	(1.59)	(2.01)	(-0.20)
more than 1,000 people				base	
			Children		
Children	0.00	-0.03	-0.04**	-0.00	-0.06*
	(0.04)	(-1.40)	(-2.12)	(-0.03)	(-1.65)
Aged 2 or younger	0.24***	0.03	-0.00	-0.07	0.02
	(2.81)	(0.54)	(-0.10)	(-0.85)	(0.40)
Aged 3-5	0.12	0.13***	0.01	0.02	-0.02
	(1.12)	(2.98)	(0.23)	(0.59)	(-0.09)
Aged 6-12	-0.04	-0.11**	-0.05	-0.02	0.10
	(-0.47)	(-2.31)	(-0.70)	(-0.33)	(1.07)
Migrant	0.06	0.04*	0.04*	0.01	-0.06
	(1.25)	(1.73)	(1.83)	(0.17)	(-1.32)
Hours worked	-0.00	-0.00***	-0.01***	-0.00***	-0.01***
	(-1.46)	(-3.97)	(-6.93)	(-4.71)	(-4.80)

Industry (NACE-1) classifications included in all regressions; observations weighted with PIAAC post-stratification weights
Significance * 0.1, ** 0.05, *** 0.01, t-statistics in brackets.

Table A.9: Quantile regressions with skills - hourly wages - results for females cont'd