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## Assessment of labour market returns in the case of gender unique human capital

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# Assessment of Labour Market Returns in the Case of Gender Unique Human Capital

Maryna Tverdostup, Tiiu Paas<sup>1</sup>

## Abstract

The paper aims to better understand the possible reasons behind gender wage disparities, focusing on the unique features of male and female human capital and their returns. Relying on the Survey of Adult Skills (PIAAC) data, we raise a research from a novel perspective towards the role of human capital in gender wage inequality. Instead of usual reference to the observable male-female characteristics' gaps, we identify the gender-unique, non-reached by the opposite gender human capital and analyse its effect on the earning profiles. The research reveals the sets of characteristics and competencies exclusive for both genders, proving that male and female profiles cannot be directly compared. Our results suggested that men possess high individual and combined abilities in numeracy and problem solving in technology rich environment, providing better earnings in spite of male average lower formal educational attainments. Wage gap analysis over the full distribution of earnings showed even larger "glass ceiling" effect for females, possessing woman-unique human capital.

**Keywords:** gender; pay differentials; human capital; matching; PIAAC

**JEL classification:** C14, J16, J24.

## 1. Introduction

The issues of gender wage inequality, its nature and possible drivers were thoroughly studied over recent decades. Various methodological approaches were employed in order to better understand the underlying reasons for male-female wage differential, identify its objective part and detect the unexplained fraction, not supported by the actual gender differences in characteristics. However, despite high research attention, resulting in enriched model specifications and rapid development of analytical tools to assess the gender pay disparity, the issue is still remaining topical, especially in the case of small and developing economies (Polachek 2009, Ćopó 2012, Anspal 2015), where labour markets are particularly sensitive to any gaps in returns to labour. Better understanding of gender wage disparities is providing additional information for development of labour market institutions and improvement of labour markets functioning.

Starting from the classical human capital model of Becker (1964), scholars focused mostly on explaining the male-female earning gap through the difference in human capital variables, arriving to the common conclusion that a substantial share of gender wage differential arises from the objective disparities in the human capital attained by males and females (Polachek 2006, O'Neill and O'Neill 2006, Grove et al. 2011, Bertrand 2011, Konrad et al. 2012, Anspal 2015). The remaining fraction of the wage differential was mostly attributed to gender discrimination (Neumark et al. 1996, Altonji and Blank 1999), however it may result from the unobserved gender heterogeneity or misspecification of an underlying model (Polachek and Kim 1994; Altonji and Blank 1999), as well as limitations of methodological approach, imposing a

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restrictive functional linearity assumption on conditional wage expectations (DiNardo et al. 1996, Nopo 2008).

Being one of key arguments in gender pay gap studies, human capital comprises a broad array of observable and unobservable characteristics. Along with various socio-demographic, educational characteristics, human capital is associated with acquired cognitive and non-cognitive abilities, significantly affecting individual labour market outcomes (Heckman et al. 2006, Roberts 2007, Ter Weel 2008, Borghans 2008). However, cognitive and non-cognitive abilities are expected to differ substantially between men and women due to difference in human capital investments, gender comparative advantages and pre-labour market discrimination (Altonji and Blank 1999).

There is a set of earlier empirical studies referring to cognitive and non-cognitive test scores, as proxies of individual competencies, in explaining men's and women's wage differences (e.g. Heckman et al. 2006; Ter Weel 2008, Cunha et al. 2008; Fortin 2008; Grove et al. 2011; Blau and Kahn 2016). However, even when accounting for the wide set of human capital components, capturing cognitive and/or non-cognitive abilities, a significant part of gender pay gap still remains unexplained and is usually attributed to unobservable factors (Christofides et al 2013). Males and females may not only differ in the set of individual characteristics, but also the distributions of those can hardly overlap, inducing the issue which is commonly referred to as "support problem" (Fortin et al. 2010). Therefore, we suppose that direct comparison of a set of average gender specific characteristics may be not enough to capture the actual difference in possessed human capital, affecting labour market outcomes of males and females. Mean value estimates provide particularly generalized picture of gender characteristics, ignoring the possible and rather expected difference in distribution of characteristics across genders (DiNardo et al. 1996, Fortin et al. 2010).

Relying on the synthesis of previous theoretical and empirical considerations, we suggest that the research can be raised from different perspective and focus on the question of "exclusive" or "specific"<sup>2</sup> human capital attainments, observed to the largest extent for certain gender. In this paper, the term "unique" or "exclusive" relates to the particular set of characteristics observed mostly among males or females. Are there such characteristics possessed by men, while non-reached by women and vice versa? How are these unique<sup>3</sup> features affecting labour market performance and contributing to explaining the gender wage disparity? These novel questions have not been profoundly addressed in previous studies, constitute a focal point of given paper. Thus, the overwhelming research aim is to better understand the possible reasons behind gender wage disparities, focusing on the unique features of male and female human capital and their returns.

We identify the gender-unique human capital in terms of two substantial arguments, mostly being neglected within previous studies. First one relates to the above mentioned gender differences in a distribution of individual characteristics. Majority of existing studies tend to explain gender wage disparity through the difference in average values of human capital variables across genders, applying parametric Oaxaca and Oaxaca-Blinder techniques (Rõõm and Kallaste 2004, Anspal et al. 2010, Grove et al. 2011, Xiu and Gunderson 2012), thus the tackled question was "What would a male earn if the compensation scheme for his individual characteristics aligned with that of a female?" (Nopo 2008, p. 290). However, such analytical

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<sup>2</sup> Terms "gender exclusive", "gender specific", "gender unique", "non-matching" across genders and "out-of-common support" human capital are used interchangeably in the paper.

<sup>3</sup> Hereinafter term "unique" or "exclusive" relates to the particular set of characteristics observed mostly among males or females. This does not rule out that same characteristics may be observed among opposite gender, but stress that they are to the largest extent possessed by either males (male-specific profile) or females (female-specific profile).

approach ignores a notion that there are also substantial differences in distribution of characteristics among males and females (Munro 1988), referred to as “comparability problem” (Rubin 1977, Heckman et al. 1997, Ñopo 2008), which results in estimation issues (Fortin et al. 2010) and overvaluing the unexplained part of the gap (Ñopo 2008).

A second aspect driving our research is a gender specific combination of human capital characteristics, rarely having a counterpart in opposite gender. Namely, there are specific combinations of characteristic of males and females, which are not always reached by opposite gender, and thus make direct, mean-value-based comparison of male-female labour market outcomes inconsistent. Being strongly interrelated with the “comparability problem” (or equivalent to it in Ñopo 2008), this issue was thoroughly addressed by Ñopo (2008) in the elaborated non-parametric matching-based decomposition technique, accounting for both difference in distribution of characteristics across compared gender subsamples and for unique combination of those in every group (“out-of-common-support” observations). Analytical approach was implemented in several studies, namely Nicodemo and Ramos (2012) applied non-parametric decomposition of given type to research the pay gap between local and immigrant women in Spain, Ñopo et al. (2012) conducted a gender wage differential study of 64 countries around the world, Anspal (2015) implemented Ñopo technique in Estonian wage gap research.

One novelty of given paper is that, starting with matching procedure based on the original Ñopo’s non-parametric decomposition technique, we go beyond a pay gap estimation and focus on the “out-of-common-support” males and females, embodying the gender specific and non-reached by opposite sex combination of characteristics, referred to as gender-unique human capital. Moreover, since our analysis relies on the Survey of Adult Skills (PIAAC) data (OECD 2013), including the estimates of cognitive abilities in literacy, numeracy and problem solving in technology-rich environment, it expands the Ñopo’s matching procedure by incorporating cognitive skills as a key dimension of individual human capital. Due to the substantial difference in skills across genders (Torben et al. 2015, Hanushek et al. 2015) we expect some cognitive abilities and their combinations to be exclusive for men while not always reached by women and vice versa, being a foundation of the unique gender specific human capital.

In conclusion, taking a different perspective to a gender pay disparities, we contribute to the existing literature on the topic by, first, extracting and analysing the gender specific unique human capital and, second, evaluating labour market returns to “out-of-common-support” males and females, representing returns to gender unique human capital, which is not always reached by the opposite sex. Since returns to the human capital may vary over the earnings distribution, we found the gender-unique human capital to provide different wage returns over the income distribution, implying a “glass ceiling” effect. Hence, we identify some non-attained by the opposite gender dimensions of a human capital as a drivers of male-female earning difference and, hence, extracting the gender unique human capital will expand a pay gap analysis framework and provide more evidence on the actual factors behind the unexplained wage disparity.

We develop our empirical study using PIAAC national database for Estonia, however, being aware of some possible limitations of the PIAAC data, compared to databases provided by more advanced surveys, e.g. the European Labour Survey (ELS) and European Social Survey (ESS). Nevertheless, PIAAC database has a considerable advantage, as it allows to link information on individual cognitive abilities with a wide range of background information on various socio-demographic characteristics of respondents.

The case of Estonia, as a small, rapidly developing European economy characterized by high rate of female labour force participation and gender wage disparities, is particularly relevant in a wage gap research framework. The estimated average male-female wage gap was c.a. 23% by the end of 2014<sup>4</sup>, being among the highest in Europe even despite substantial decrease over recent years (Anspal 2010, Meriküll and Mõtsmees 2015), while rate of female employment exceeds average European level (c.a. 72% of female population aged 15-64 years, compared to 66% average participation over Euro area in 2013<sup>5</sup>). Therefore, we believe that Estonian case study will allow to make certain generalizations for other relatively quickly developing economies, where women's labour participation rate is high and/or has a tendency to increase.

The issue of gender wage gap in Estonia has been already rather widely studied by the Estonian and foreign researchers, namely Rõõm and Kallaste (2004), Masso and Krillo (2011), Anspal et al. (2010), Christofides et al. (2013), Vassil et al. (2014), Meriküll and Mõtsmees (2015), Anspal (2015). The estimates of explained fraction of the pay gap on average varied between 10 and 44 percent, in various specifications, controlling for individual demographic, educational characteristics, occupation variables. However substantial share remained unexplained and mostly assigned to potentially important factors, which are not captured by the data or provided in insufficient detail (Anspal et al. 2010, Vassil et al. 2014, Anspal 2015). Thus, the variability of the previous research results also indicates that the issue of gender wage disparity requires additional research attention, incorporating implementation of novel methodological approaches and using information from various databases.

The rest of the paper is organized as follows. Section 2 presents an overview of the Survey of Adult Skills (PIAAC) data as well as the main analytical tools implemented for empirical analysis. Section 3, with three sub-sections, presents the main results on female- and male-unique characteristics and their wage returns, followed by the summary and discussion of key findings in section 4.

## **2. Data and Empirical Strategy**

The data used in our analysis was collected within a Survey of Adult Skills, as a part of the Programme for the International Assessment of Adult Competencies (PIAAC), currently implemented in 24 countries, including 22 OECD member states. The survey assessed proficiency in literacy, numeracy and problem solving in technology-rich environments of adults aged 16-65 year. Along with the key information-processing assessments, survey provides a wide range of background information on the basic socio-demographic characteristics of respondents, their educational attainments, participation in education and training, labour force status, employment characteristics. Representative samples were questioned in years 2011-2012 and first results were published in 2013 (OECD 2013).

Since we conduct the Estonian case-study analysis, we rely on Estonian public use data file, including a random sample of 7632 survey respondents. We limit our analysis to full-time salaried workers (employers, self-employed and family workers are excluded), for whom associated monthly wage without bonuses is observed. Despite quite a low rate of self-employment activity in Estonia (PIAAC data reports c.a. 8% for Estonia and c.a. 10% for Nordic states overall) excluding employers, self-employed and family workers from the analysis will eliminate a possible fraction of the pay gap resulting from men's higher self-employment participation (c.a. 70% of self-employed are males).

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<sup>4</sup> Estimated by Statistics Estonia. Source: <https://www.stat.ee/90587>

<sup>5</sup> Estimated by the World Bank. Source: <http://databank.worldbank.org/data/reports.aspx?source=283>

Thus, our final sample includes 3411 observations, of whom 1520 are men and 1891 women. The dependent variable is monthly earnings without bonuses and additional payments for full-time employed respondents<sup>6</sup>. Within the final sample, 77 respondents have wage variable, derived through the imputation procedure relying on the original self-reported earnings in broad categories. We performed additional robustness checks in order to verify that including the respondents with derived earnings variable will not affect the reliability of estimates.

Our econometric model controls for a set of traditional socio-demographic characteristics, along with cognitive abilities in three domains, evaluated within the Survey of Adult Skills (OECD 2012). Survey participants were tested in literacy, numeracy and problem solving in technology rich environment domains and results were scaled from 0 to 500 points<sup>7</sup>. As a proxy for individual level of skills the first plausible value was considered for every domain, similar to Hanushek et al. (2015) and Anspal (2015). Initial continuous skill variables were transformed to interval variables, reflecting the level of skill attained (below 176, 176-226, 227-276, 277-326, 327-376, above 376 points). Being aware of possible multicollinearity arising from simultaneous including of all skill variables in the model, we accomplish regression analysis with a variance inflation factor (VIF) test.

Given that in Estonia around 31% of PIAAC respondents refused to take a computer-based assessment and thus complete a set of task on problem solving skills, observations with missing problem solving score will be eliminated from the analysis. Since among those with problem solving score missing gender proportion is almost even (47% are males), excluding these respondents from the analysis is not likely to cause gender bias. The average cognitive skills estimates, along with other descriptive statistics of the total sample are presented in Appendix 1.

Following the aim of the research we first extract from the total sample of full-time employed respondents males and females possessing a set of characteristics, non-reached by the opposite gender, referred to as gender unique samples. Identification method relies on a matching procedure, elaborated by Ľopo (2008) within non-parametric wage gap decomposition framework. Since earlier matching based decomposition approaches encountered several limitations, namely relying on the propensity scores instead of matching on characteristics (Black et al. 2004) and omitting the “out-of-common-support” observations (Pratap and Quintin 2002), the approach suggested by Ľopo is the most consistent with our research task, as it estimates the wage gap on a full distribution of control variables across genders and thus accounts for both matched (“in-common-support”) and non-matched (“out-of-common-support”) with respect to a set of defined characteristics men and women.

A complete functional form of Ľopo’s pay gap decomposition is the following<sup>8</sup>:

$$\Delta = \Delta_M + \Delta_x + \Delta_O + \Delta_F. \quad (1)$$

The components of (1) are:

- part of a gap arising from a difference in characteristics of males having characteristics matched to women’s and those with non-matched profiles

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<sup>6</sup> Elimination of outliers, namely respondents below minimum wage of year 2012 rate (278 EUR) and with earnings above 5000 EUR (total 54 observations) did not change the wage gap estimates significantly. Thus further analysis relies on a full wage distribution.

<sup>7</sup> For more detailed information on survey construction and skills assessment see OECD (2013). “Technical Report on the Survey of Adult Skills (PIAAC)”. *OECD Publishing*. [http://www.oecd.org/site/piaac/Technical%20Report\\_17OCT13.pdf](http://www.oecd.org/site/piaac/Technical%20Report_17OCT13.pdf)

<sup>8</sup> For the explicit derivation procedure see Ľopo, H. (2008). “Matching as a Tool to Decompose Wage Gaps.” *The Review for Economics and Statistics*, 90(2): 290-299.

$$\Delta_M = \left[ \int_{\overline{S^F}} g^M(x) \frac{dF^M(x)}{\mu^M(\overline{S^F})} - \int_{S^F} g^M(x) \frac{dF^M(x)}{\mu^M(S^F)} \right] \mu^M(\overline{S^F}); \quad (2)$$

– fraction explained by the observable difference in male and female characteristics

$$\Delta_x = \int_{S^M \cap S^F} g^M(x) \left[ \frac{dF^M}{\mu^M(S^F)} - \frac{dF^F}{\mu^F(S^M)} \right] (x); \quad (3)$$

– the share unexplained by observable characteristics and thus attributed to both difference in unobservable characteristics and discrimination

$$\Delta_o = \int_{S^M \cap S^F} [g^M(x) - g^F(x)] \frac{dF^F(x)}{\mu^F(S^M)}; \quad (4)$$

– part of a wage gap resulting from a difference in “matched” and “non-matched” females characteristics

$$\Delta_F = \left[ \int_{S^M} g^F(x) \frac{dF^F(x)}{\mu^F(S^M)} - \int_{\overline{S^M}} g^F(x) \frac{dF^F(x)}{\mu^F(\overline{S^M})} \right] \mu^F(\overline{S^M}), \quad (5)$$

where  $X = \{x_i\}$  is a vector of individual characteristics controlled for in a model,  $F^M(\cdot)$  and  $F^F(\cdot)$  denote cumulative distribution functions of individual characteristics  $X$  conditional on being a man or a woman respectively. Thus  $dF^M(\cdot)$  and  $dF^F(\cdot)$  are corresponding probability measures, while  $\mu^M(x)$  and  $\mu^F(x)$  capture the probability measure for a total sample  $S$  under the respective distributions  $dF^M(\cdot)$  and  $dF^F(\cdot)$ . The dependent variable, being monthly earnings of full-time employed respondents, is seized by functions  $g^M(\cdot)$  and  $g^F(\cdot)$ , indicating expected wage conditional on gender and individual characteristics  $X$ . Reflecting a key idea of the decomposition technique,  $S^M$  and  $S^F$  represent supports of the distribution of characteristics for males and females (“in-common-support” part of sample) and  $\overline{S^M}$  and  $\overline{S^F}$  denote “out-of-common-support” distribution of men’s and women’s characteristics.

Since our analysis focuses on “out-of-common-support” males and females,  $\overline{S^M}$  and  $\overline{S^F}$  gender sub-samples are of the main research interest, as they possess characteristics, non-reached by the opposite gender. Under this framework, from equations (2) and (5) we respectively define an average wage of the non-matched, or unique in our definition, males and females as:

$$E[Y|M \in \overline{S^M}] = \mu^M(\overline{S^F}) \cdot \int_{\overline{S^F}} g^M(x) \frac{dF^M(x)}{\mu^M(\overline{S^F})} \quad (6)$$

and

$$E[Y|F \in \overline{S^F}] = \mu^F(\overline{S^M}) \cdot \int_{\overline{S^M}} g^F(x) \frac{dF^F(x)}{\mu^F(\overline{S^M})}, \quad (7)$$

where  $Y$  denotes earnings level and  $M, F$  – male and female respondents respectively.

To identify “out-of-common-support” men and women, we perform a matching procedure on a set of characteristics, which directly determine individual human capital (formal education attained and literacy, numeracy and problem solving abilities) or are believed to have a strong impact on human capital accumulation (age, first generation immigrant status). There is a clear one direction causal relationship between the last two controls and actual level of human capital attained by an individual, not necessarily being a case with other possible controls, e.g. self-assessed health condition, years of work experience, set of employment characteristics, including occupation held, industry of employment etc. However, in order to ensure the robustness of our matching framework, we additionally performed matching on the extended list of controls, including marital status, occupation and industry of employment, presented in part 5 of the paper.

Despite a majority of wage gap studies (Polachek, Xiu and Gunderson 2012, Anspal 2015) control for occupation characteristics when decomposing pay difference, we will follow the original argument of Oaxaca (1973), assuming that occupation may already be a result of discrimination, referred to as the “pre-labor market discrimination”. Omitting the occupational and other related employment characteristics allow to evaluate a gender pay disparity relative to merely individual human capital components, keeping a possible occupational barrier as one of the discrimination sources.

Based on the derived gender unique samples  $\overline{S^M}$  and  $\overline{S^F}$  – focus group of our analysis – we further analyse their key characteristics individually and combinations of those to see what are the aspects of males’ and females’ human capital not always reached by opposite gender. For more complete idea of unique sample characteristics, we additionally examine respective variables within the control group – “in-common-support” male and female samples  $S^M$  and  $S^F$  – with further comparison across unique and matched samples of both genders.

Since the fundamental idea behind Ñopo’s matching methodology is in identifying matched and non-matched characteristics across gender, with those classified as non-matched being unique within certain gender, the difference in labour market outcomes of males and females equipped with a set of skills, exclusive for their gender, can not be evaluated applying traditional decomposition techniques. Tremendous difference in distribution of characteristics of gender-unique subsamples will result in inconsistent gap estimates under the decomposition methodologies, driven by linearity assumptions and relying on mean estimates (like Oaxaca or Oaxaca-Blinder approach), while non-parametric techniques cannot be implemented by definition, as compared  $\overline{S^M}$  and  $\overline{S^F}$  samples have non-matching characteristics.

Therefore, the disparity in wage returns to gender exclusive human capital, with a special emphasis on gender-unique cognitive abilities’ role in earnings formation, can be analysed separately in men’s and women’ unique samples. Although a key conclusions can be derived already from usual OLS wage regressions, controlling for age, age squared, first generation immigrant status, formal education and three skill domains, we apply quantile regression approach, to see the effect of skills as a main component of gender exclusive profile on a full wage distribution, but not only at mean earnings.

As a key tool for analysis of wage disparities over a full wage distribution, quantile decomposition was previously applied by Melly (2006), Christofides et al. (2013), Meriküll and Mõtsmees (2015) in wage gap studies. As discussed above, nature of derived gender unique samples  $\overline{S^M}$  and  $\overline{S^F}$  does not allow to directly examine pay gap of those, hence we refer to a quantile regression technique to estimate separate quantile wage regressions in gender specific unique samples  $\overline{S^M}$  and  $\overline{S^F}$ . The regression is set up in terms of minimizing a sum of squared residuals in order to estimate a conditional function at  $\tau$  quantile of the following form:



$$Q_\tau(y_i|x_i) = \arg \min_{q(x)} E[\rho_\tau(y_i - q(x))], \quad (8)$$

where  $Q_\tau(y_i|x_i)$  is a conditional  $\tau$ -quantile function of dependent variable  $y_i$  given a vector of regressors  $x_i$  and  $q(x_i)$  is a linear function of regression model parameters<sup>9</sup>. Thus, the quantile regression estimator  $\beta_\tau$  can be produced as:

$$\beta_\tau = \arg \min_b E[\rho_\tau(y_i - x_i'b)]. \quad (9)$$

Quantile regression will be applied for both evaluation of female and male returns to unique human capital and assessment of wage returns to particular characteristics within gender-unique profiles over a full distribution. To highlight the advantage of quantile approach we replicate models' estimation with usual ordinary least squares (OLS) technique.

### 3. Empirical Results

#### 3.1. Matching and extraction of the gender-unique human capital

To extract from the overall sample respondents possessing female- and male-unique characteristic, we first perform a decomposition exercise following Ñopo's approach. As previously discussed, decomposition model controls solely for age, immigrant status, formal education and three domains of cognitive skills. Therefore, matching across genders was done with respect to these characteristics merely<sup>10</sup>.

**Table 1.** Gender pay gap decomposition

Decomposition technique	Wage gap decomposition					Matched females		Matched males	
	$\Delta$	$\Delta_O$	$\Delta_X$	$\Delta_F$	$\Delta_M$	%	N	%	N
Non-parametric (Ñopo)	0.5888	0.5727	-0.0243	-0.0401	0.0804	57.7	1092	61.6	936
Parametric (Oaxaca-Blinder)	0.5840	0.5980	-0.0140				1398		1087

Note: Dependent variable is log monthly earnings of full-time employed. The model controls for age, age squared, first generation immigrant status, formal education attained, literacy, numeracy and problem solving score.

Table 1 presents the Ñopo-type pay gap decomposition of a specified model, along with estimates of classical Oaxaca-Blinder decomposition<sup>11</sup> on the total sample. The overall gender pay gap identified by applying non-parametric decomposition is 58.9% with 57.3 p.p. (97.3% of overall gap) unexplained, while under parametric approach unexplained part of a pay differential constitutes 59.8 p.p. in overall gap of 58.4%. Thus, Oaxaca-Blinder technique, relying on assumption of functional linearity and wage gap estimation at means of variables' distributions, clearly overestimates unexplained part of a wage difference. Under Ñopo's approach, these two assumptions are relaxed and "support problem" is accounted for, resulting in more precise decomposition estimates.

Since our research attention is on the "out-of-common-support" sample of males and females, we now focus on those 42.3% of females and 38.4% of males for whom there was no profile match found among the opposite gender (with respect to characteristics specified in decomposition model). These respondents embody the non-overlapping with opposite gender characteristics, referred to as female- and male-unique human capital. Estimated wage gap

<sup>9</sup> For the explicit derivation procedure see Koenker, R., Hallock, K. (2001). "Quantile Regression: An Introduction". *Journal of Economic Perspectives*, 15: 143–156

<sup>10</sup> Appendix 2 presents a number of alternative decomposition model specifications to ensure the robustness of our results, estimated with both non-parametric (Ñopo-style) and parametric (Oaxaca\_Blinder) techniques

<sup>11</sup> For the methodology description see Oaxaca, R. (1973). "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review*, 14(3): 693-709

components  $\Delta_F$  and  $\Delta_M$  suggest that both men (by c.a. 8%) and women (by c.a. 4%) with gender-unique characteristics benefit relative to those, having characteristics comparable to the opposite gender. However, we further aim to explicitly analyse the components and wage returns of female- and male-unique human capital.

### 3.2. Exclusive human capital attained by males and females

Table 2 reports means of the variables controlled for in wage decomposition and matching procedure estimated for “out-of-common-support” male and female samples ( $\bar{S}^F$  and  $\bar{S}^M$ ) as well as “in-common-support” observations ( $S^F$  and  $S^M$ ). Appendix 3 includes descriptive characteristics of “out-of-common-support” men and women, defined under matching procedure with extended list of variables. Including additional controls did not affect substantially the gender-unique profiles, ensuring robustness of a basic matching procedure.

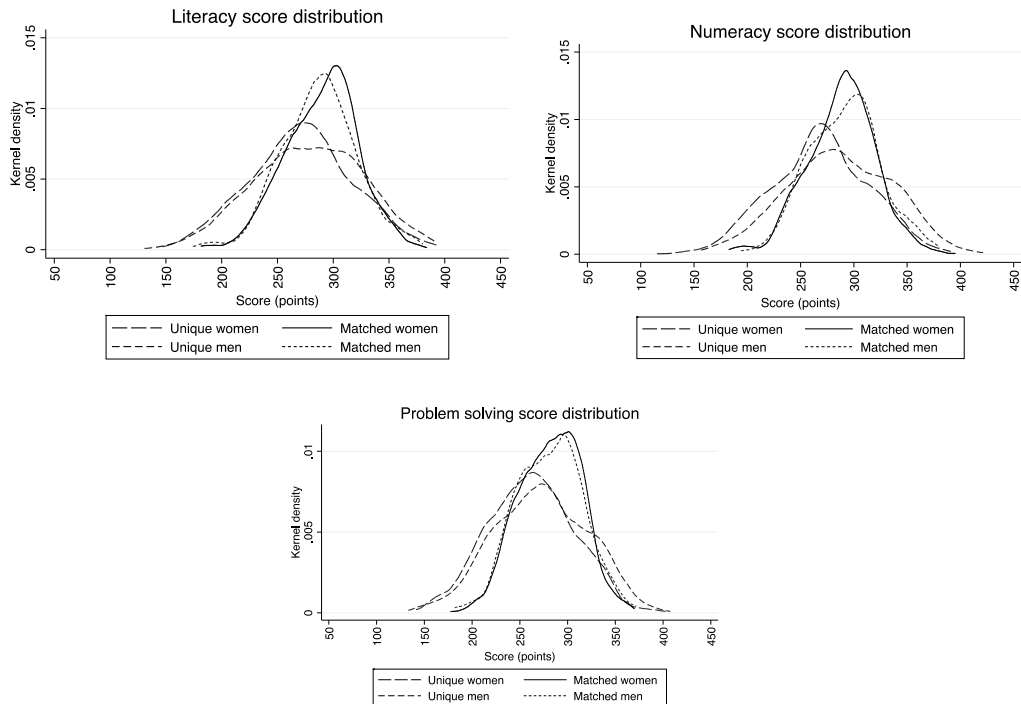
**Table 2.** Descriptive statistics for gender unique human capital

Variable	"Unique" sample		"Matched" sample	
	Female $\bar{S}^F$	Male $\bar{S}^M$	Female $S^F$	Male $S^M$
Average age, years	43	38	38	37
Immigrant in 1st generation, %	12.4	11.1	2.3	2.8
Educational level, %				
- Higher education	59.3	33.2	55.7	47.2
- Secondary education	33.8	49.1	40.4	47.4
- Basic education	6.9	17.6	3.9	5.4
Cognitive skills, points				
- Literacy	271	278	289	287
- Numeracy	268	286	288	290
- Problem solving	262	272	282	281
Average wage, EUR	787	1282	848	1292
Absolute wage gap, EUR	495		444	
Wage gap relative to women's earnings, %	62.9		52.4	
<b>Number of observations</b>	<b>799</b>	<b>584</b>	<b>614</b>	<b>517</b>

Overall, the descriptive statistics reveals a substantial difference in female- and male-unique profiles. Non-matched men, despite lower formal education, have higher cognitive skills in all dimensions, compared to non-matched women. Average numeracy score of unique men's sample is 18 points higher, compared to respective skill estimate of unique women. Problem solving score difference in  $\bar{S}^M$  and  $\bar{S}^F$  samples is 10 p.p. in favour of males, while literacy attainments are on average 7 p.p. higher among males, possessing exclusive characteristics. However, educational achievements are substantially better for females with exclusive for their gender characteristics (59.3% of unique women hold university degree, while only 33.2% among unique men).

Naturally, comparing unique males and females with men and women, having human capital matched to opposite gender, disclosed more substantial differences between unique men and women, while estimated means for matched males and females are nearly equal. It strengthens credibility of our estimates and additionally ensures robustness of a matching procedure, as “in-common-support” sub-samples of males and females possess comparable distributions of individual characteristics.

Our findings indicate that despite women clearly over-perform men in terms of formal educational attainments, males have outstanding competitiveness in numeracy and problem solving, compared to females, since high results in these skill domains are more frequently reached by men. These exclusively high numeracy and problem solving abilities constitute one of the main components of men’s human capital “uniqueness” and strong advantage relative to women, potentially providing better earning profile in spite of men’s on average lower formal educational attainments.



**Figure 1.** Kernel densities of literacy, numeracy and problem solving score distribution among matched and unique males and females (matching on the set of socio-demographic, educational characteristics and cognitive skills)

Figure 1 provides supplementary evidence of substantial differences in distributions of male and female characteristics. Reported distributions of attained scores in all skills domains showed that a men-women score gap in a high results range is much larger between unique samples, relative to matched. The largest differential is observed in numeracy score distribution, which goes in line with previous PIAAC-based findings (Torben et al. 2015).

To give more credibility to the findings, we perform a two-sample Kolmogorov-Smirnov test to verify that male-female difference in skills distributions persists. Appendix 4 displays the estimates of Kolmogorov-Smirnov test on the “out-of-common-support” and “in-common-support” samples, rejecting a zero-hypothesis of no difference in the distributions of skills among unique males and unique females at  $p = 0.01$ . Thus, our results suggest that outstanding cognitive abilities possessed by men is the major source of a male-exclusive human capital.

However, skills distribution density analyses captures a single skill dimension over compared groups, without reflecting their combinations, which potentially may hardly overlap between men and women, being another source of the gender exclusive human capital. Given that the gender-unique samples were extracted through performing male-female matching on a set of characteristics, we expect the combinations of skill distinctive for men or women solely, to be even stronger driver of male-female human capital disparity. Table 3 presents estimated

frequencies of different combinations of numeracy and problem solving capabilities among men and women, having no matching characteristics in the opposite gender<sup>12</sup>.

**Table 3.** Distribution of numeracy and problem solving skills' combinations across gender

“Unique” males, % <sup>1</sup>						“Unique” females, % <sup>1</sup>					
<i>Numeracy</i>	<i>Problem solving</i>					<i>Numeracy</i>	<i>Problem solving</i>				
	176-226	227-276	277-326	327-376	Total		176-226	227-276	277-326	327-376	Total
<b>176-226</b>	5.88	3.31	0.18	0	<b>9.38</b>	<b>176-226</b>	9.13	6.61	0.26	0	<b>16.01</b>
<b>227-276</b>	8.27	16.36	6.80	0.37	<b>31.80</b>	<b>227-276</b>	8.60	23.28	9.52	0.40	<b>41.80</b>
<b>277-326</b>	1.84	15.99	13.79	4.41	<b>36.03</b>	<b>277-326</b>	1.59	11.64	12.70	4.89	<b>30.82</b>
<b>327-376</b>	0	2.21	10.85	9.74	<b>22.79</b>	<b>327-376</b>	0	0.79	7.41	3.17	<b>11.38</b>
<b>Total</b>	<b>15.99</b>	<b>37.87</b>	<b>31.62</b>	<b>14.52</b>	<b>100</b>	<b>Total</b>	<b>19.31</b>	<b>42.33</b>	<b>29.89</b>	<b>8.47</b>	<b>100</b>

<sup>1</sup> Respondents with numeracy and/or problem solving scores less than 176 or higher than 376 points were eliminated from the sample (40 males and 42 females). Frequencies are estimated relative to the sample, excluding these outliers.

The results indicate that along with significant disparity in distribution of individual skill scores in “out-of-common support” gender sub-samples, combinations of individual competitiveness in numeracy and problem solving domains differ a lot. Overall, for “non-matched” males numeracy score ranked in the highest considered interval (327-375 points) is more often attained, compared to “non-matched” females. Thus the “best” in given set-up cognitive skills profile, comprising those individuals with both numeracy and problem solving scores falling in the highest interval, is reached by respectively 9.7% and 3.2% of unique males and females.

Frequencies displayed in Table 3 suggest more smooth distribution of male-exclusive numeracy and problem solving skills combinations, relative to female-exclusive, over a full score interval. Correlations of these two cognitive abilities, mapped across “out-of-common support” and “in-common support” gender samples (see Appendix 5), support this assumption. Namely, combinations of numeracy and problem solving scores observed in unique men’s sample are evenly plotted over all possible score range, with relatively same frequency in both “low” and “high” ends for both cognitive abilities, while unique women’s combined scores are clustered at the average result range (c.a. 230-280 points) and have higher density at a “lower” end. This observation provides another evidence that male-exclusive human capital is at large extent embodied in combination of the outstanding cognitive abilities, being a strong competitive advantage of males often non-reached by females.

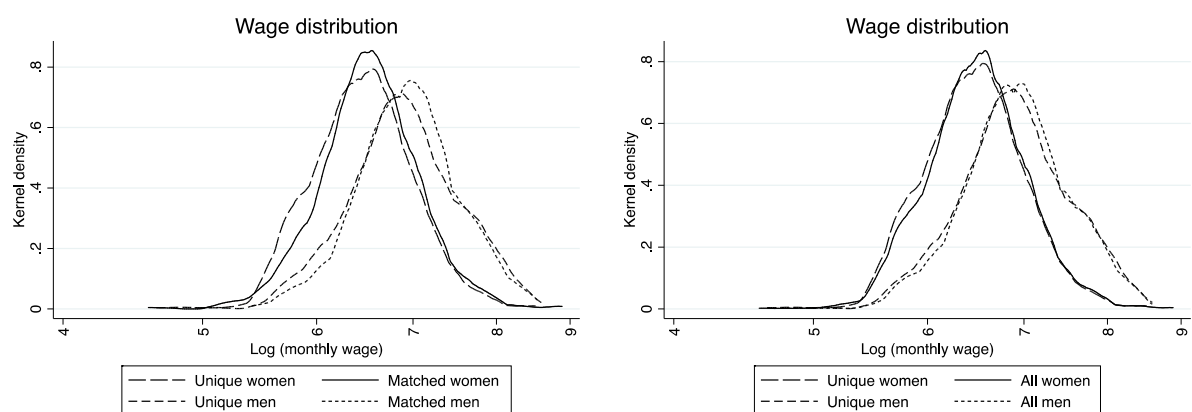
These higher single and combined skills attainments, exclusive for males, may be one of the key factors driving a wage level of men upwards. As reported in Table 2, gender pay gap between “out-of-common-support” males and females is 63%, while in matched sample it constitutes 52%, implying that male-exclusive qualities are particularly valuable in a labour market and provide higher wage returns, relative to men with characteristics comparable in their distribution to the ones of women.

### 3.3. Gender-unique human capital and its effect on labour market outcomes of men and women

Based on our findings, we further aim to investigate how earnings of men and women, possessing exclusive for their genders characteristics, differ and in which way earnings are contingent on these unique qualities.

<sup>12</sup> Based on descriptive estimates provided in Table 2, we have identified numeracy and problem solving as two key domains of cognitive abilities, substantially contrasting between males and females.

Figure 2 presents the distribution of earning level attained by men and women having characteristics exclusive for their gender, relative to their males and females with comparable profiles and total sample. Constructed kernel densities reveal that wage returns to the gender-unique profile, relative to gender-comparable, differ for men and women. “Out-of-common-support” men are more often at higher rates, while females with unique set of characteristics are in higher wage categories less frequently, compared to “in-common-support” peers. This finding indicates that labour market responds differently to the women- and men-unique characteristics, giving additional support to our hypothesis that males possess highly valuable by labour market characteristics, non-reached by females.



**Figure 2.** Kernel densities of wage distribution of matched, unique and total sample of males and females

Thus, among individuals possessing unique for their gender characteristics, men are still earning higher wages. Since, the wage rates of unique males and females cannot be directly compared, as a distribution of individual characteristics and their combination is different in gender-specific unique samples, applying parametric techniques (e.g. Oaxaca-Blinder procedure) for estimation of explained and unexplained fractions of an observed differential is not consistent. To analyze how gender unique profiles affect male and female possessors’ labour market outcomes, we first model a wage difference in focus sample (unique men and women) and control group, being men and women with comparable characteristics (matched samples).

**Table 4.** Female coefficients in usual OLS and quantile wage regressions

Female wage gap	OLS <sup>1</sup>	Quantile regression					N
		10th	25th	50th	75th	90th	
"Unique" sample	-0.461 (.0200)***	-0.269 (.0464)***	-0.373 (.0376)***	-0.449 (.0220)***	-0.564 (.0347)***	-0.750 (.0785)***	1102
VIF <sup>2</sup>		Literacy and numeracy		2.17			
		Literacy and problem solving		1.98			
		Numeracy and problem solving		1.90			
"Matched" sample	-0.442 (.0247)***	-0.396 (.0580)***	-0.373 (.0310)***	-0.446 (.0332)***	-0.519 (.0328)***	-0.520 (.0599)***	1102
VIF <sup>2</sup>		Literacy and numeracy		2.27			
		Literacy and problem solving		1.90			
		Numeracy and problem solving		2.02			

<sup>1</sup> OLS survey regressions with standard errors estimated using Jackknife replication methodology

<sup>2</sup> VIF test was estimated from individual survey OLS regressions with literacy, numeracy and problem solving skills as dependent variables. After for every regression VIF was computed manually as inverse to tolerance, namely  $1/(1 - R^2)$ .

Note: Dependent variable is log monthly earnings of full-time employees. The models additionally controls for age, age squared, first generation immigrant status, formal education attained, literacy, numeracy and problem solving scores. \*\*\*, \*\*, \* Indicate parameters significant at 1%, 5% and 10% levels respectively.

Following arguments, discussed in Section 2, we do not implement wage gap decomposition, but estimate usual OLS and quantile wage regressions in control and focus groups. Table 4 presents coefficients of female dummy variable, being of a main research interest, as it represents the actual difference between male and female earnings in given samples and model specifications, as well as variance inflation factor test (VIF) estimates to check for possible correlation of different dimensions of cognitive skills.

Overall, the results revealed substantial variation of male-female pay gap over full wage distributions, therefore the estimates from usual OLS regression does not provide sufficient evidence to compare focus and control groups. While regular OLS shows that in the focus sample, women possessing unique characteristics earn 46.1% lower wage, relative to men with male-exclusive profile, in the matched control group overall wage disparity is c.a. 2 p.p. lower. Estimated VIF test verify that multicollinearity is of insignificant magnitude (of an order less than 10), thus further analytical models will comprise all three skill variables simultaneously.

As it was expected, regression estimates along a full wage distribution, provide more comprehensive picture on gender pay gap relative to earning rates. Our findings indicate that pay dispersion between males and females equipped with exclusive for their gender characteristics varies more dramatically across earnings distribution, compared with the one estimated for men and women with comparable human capital features. Namely, in the unique sample female pay gap at lower conditional wage quartile is considerably smaller (26.9%), compared to matched group (39.6%), implying that at low earning rate unique set of female characteristics provides higher wage returns, compared to females with human capital characteristics matched with males'.

However, the reverse holds in upper quantiles. Namely, in 90<sup>th</sup> percentile of conditional wage distribution women pay gap in unique sample is 75%, being 23 p.p. larger than in the control group. The result indicates that among high-earners female-unique human capital provide lower returns compared to the male-comparable characteristics possessed by women. This observation gives strong evidence of even larger “glass ceiling” effect<sup>13</sup> for unique females than matched, as gender pay gap measured in upper conditional wage quantile between men and women possessing gender unique characteristics exceeds the one estimated for men and women with matching profiles. It goes in line with findings of Christofides et al (2013), Meriküll et al. (2015), reporting the “glass ceiling” effect for the Estonian labour market.

However, our analysis revealed it to be even more substantial for females with characteristics not observed among males. It provides additional evidence for pay gap analysis, as women-unique characteristics are less valuable at a labour market, than male-unique, leading to a naturally higher wage returns of men. In the traditional Oaxaca-Blinder parametric set up, this effect was captured by “unexplained” fraction of a total wage differential. As discussed in Section 2, possible estimation bias may arise from including 77 respondents with derived wage variable. Therefore, we performed a robustness check by replicating the same regression analysis on the sample restricted to the respondents with self-reported earnings. The results, enclosed in Appendix 6, revealed that there is are no substantial differences with the parameters, reported in Table 4, supporting a credibility of the estimates based on the full sample.

As our previous results showed that male-exclusive human capital is induced by outstanding cognitive skills and combinations of those, not always attained by females, a natural question arising is what is an actual contribution of the males' unique competencies to their earning profile. Similarly to analysis of the wage differential between unique men and women, we apply first usual OLS regression to estimate contribution of individual cognitive skills over a full

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<sup>13</sup> Extensively studied by Albrecht et al. (2003) and (2009), Xiu and Gunderson (2012).

distribution of wages and, second, use conditional quantile regression approach to see how earning are contingent on cognitive abilities in different quantiles of wage distribution.

**Table 5.** Cognitive skills coefficients in usual OLS and quantile wage regressions

Skill variables (group score) <sup>1</sup>	OLS <sup>2</sup>	Quantile regression <sup>3</sup>				
		10th	25th	50th	75th	90th
<b>“Unique” males</b>						
Literacy	-0.0484 (.0246)**	-0.0554 (.0479)	-0.02 (.0421)	-0.0378 (.0386)	-0.0948 (.0521)	-0.0222 (.0718)
Numeracy	0.1001 (.0287)***	0.1524 (.0506)***	0.1052 (.0415)***	0.1053 (.0322)***	0.1144 (.0502)*	0.1029 (.0598)
Problem solving	0.0723 (.0287)***	0.0284 (.0442)	0.0531 (.0378)	0.0824 (.0388)**	0.1236 (.0569)***	0.027 (.0825)
N of observations	503					
<b>“Matched” males</b>						
Literacy	-0.0852 (.0318)**	-0.030 (.0762)	-0.0438 (0.0892)	-0.0491 (0.0554)	-0.1668 (0.0809)**	-0.0894 (0.0778)
Numeracy	0.1667 (0.0314)***	0.166 (0.0836)**	0.1689 (0.0898)*	0.1739 (0.0869)**	0.188 (0.0706)***	0.0715 (.0631)
Problem solving	0.0829 (.0290)***	0.0678 (.0957)	0.0791 (.0613)	0.0286 (.0903)	0.1256 (.1033)	0.0956 (0.0894)
N of observations	503					
<b>“Unique” females</b>						
Literacy	0.0674 (.0191)***	0.138 (.0554)**	0.0748 (.0458)*	0.0572 (.0318)**	0.0573 (.0450)	0.021 (.0550)
Numeracy	0.0447 (.0235)*	0.089 (.0419)**	0.0573 (.0430)	0.0411 (.0387)	0.0286 (.0452)	0.0425 (.0393)
Problem solving	0.0561 (.0172)***	-0.0232 (.0446)	0.0334 (.0295)	0.051 (.0465)	0.0772 (.0379)*	0.1209 (.0516)***
N of observations	599					
<b>“Matched” females</b>						
Literacy	0.0323 (0.0284)	0.0846 (.0937)	0.0268 (.0568)	0.0269 (.0468)	0.0426 (.0859)	0.0839 (.1711)
Numeracy	0.0824 (.0303)***	0.1786 (.1010)*	0.115 (.0727)	0.0848 (.0525)	-0.003 (.0669)	0.0008 (.1257)
Problem solving	0.1169 (.0288)***	-0.0746 (.1054)	0.0654 (.0391)*	0.0886 (.0479)*	0.1401 (.0828)*	0.1767 (.1219)
N of observations	599					

<sup>1</sup> Interval variable (0-175, 176-225, 226-275, 276-325, 326-375, 376-500 points)

<sup>2</sup> OLS regressions with standard errors estimated using Jackknife replication methodology

<sup>3</sup> Simultaneous conditional quantile regression with standard errors and confidence intervals obtained with bootstrapping method

Note: Dependent variable is log monthly earnings of full-time employees. The models additionally controls for age, age squared, first generation immigrant status, formal education attained. \*\*\*, \*\*, \* Indicate parameters significant at 1%, 5% and 10% levels respectively.

Based on the usual OLS approach, “out-of-common-support” males were found to favour only from higher numeracy and problem solving abilities (10% and 7.2% wage increase associated with moving to a next higher score interval), while higher literacy score relates to 4.8% wage

decrease. By comparison, “out-of-common-support” females benefit from all the skills (6.7%, 4.5% and 5.6% wage gain associated with every higher literacy, numeracy and problem solving score interval respectively), however magnitudes of positive returns to numeracy and problem solving are lower, compared to male-unique profile. In line with our previous findings, OLS estimates support an assumption that main components of male-unique human capital, being highly valued by a labour market, are numeracy and problem solving cognitive abilities.

Further look at the men-unique skills effects in separate quantiles of conditional wage distribution, reveals that high numeracy ability benefit the most at lower quantiles, i.e. among low-earners higher numeracy score is associated with more substantial wage increase (15.2% and 10.5% in 10<sup>th</sup> quantile and median of conditional wage distribution respectively). However, a role of problem solving competence increases along wage distribution and the largest benefit is observed in 75<sup>th</sup> quantile (12.4%), capturing those with earnings higher than average, while for unique females problem solving skills matter the most at the very top of wage distribution (12.1% wage increase associated with better level of problem solving abilities in the 95<sup>th</sup> quantile).

In the sample of males and females with gender-comparable characteristics, returns to skill domain differ. Namely, for matched males observed returns to numeracy skills were higher over the whole wage distribution, while returns to higher problem solving ability was statistically not significant over separate earnings quantiles. Matched females, on the contrary, benefit from higher problem solving scores on the middle of wage distribution (6.5%, 8.9% and 14% wage increase in 25<sup>th</sup>, 50<sup>th</sup> and 75<sup>th</sup> quantiles respectively).

#### **4. Conclusions and Discussion**

Gender wage gap has been an issue attracting researchers from different fields and countries for decades. As a rule, empirical evidence showed that unexplained part of a gender wage differential is high and cannot be explained by the measured traditional socio-economic characteristics of employees, implying that several other unobservable cognitive and non-cognitive features are playing a remarkable role in gender wage disparities. The outcomes of previous empirical studies were rather unstable, being also sensitive to the implemented methods and data sources. The novelty of given study is not only in application of the PIAAC database allowing to measure individual cognitive abilities in literacy, numeracy and problem solving, but also in the number of implemented methodological approaches towards identifying a role of human capital in wage inequalities.

The main contribution of the given research is a novel approach towards the role of human capital in gender wage disparity. Instead of usual reference to the observable male-female difference in characteristics, in this paper the unique, non-reached by the opposite gender human capital is identified and its effect on the earning profiles of unique human capital holders is analysed. In our research, relying on decomposition procedure irrelevant to functional linearity assumptions, we go beyond a pay gap decomposition and focus on the “out-of-common-support” men and women, as they possess exclusive characteristics and their combinations, non-reached by the opposite gender, representing the gender unique human capital.

While in most of the previous studies a gender difference arising from variation of cognitive skills across males and females was assigned to unexplained part of a wage differential, the analytical approach elaborated within a given paper both extract and explicitly analyse the gender-unique profiles and thus contribute to gender pay gap studies by evaluating the wage returns to male- and female-exclusive characteristics. The results showed that a subsample of unique males have cognitive abilities at a level that females mostly do not reach, thus their



superior earnings appear as a premium to their better competencies. Skills are valued at a labour market more than formal education, hence men's better numeracy and problem solving abilities help them to attain higher wage, despite lower formal education.

Not solely skills, but their combinations, matter a lot in a valuation of the human capital and analysing the effect on the labour market outcomes. Therefore, the unique combination of skills, as a main component of the human capital, reached by males and females and unattained by opposite gender is one of the key sources of gender disparity in a human capital. As this assumption was extensively addressed in a given paper, the results revealed that male-unique human capital is at large extent embodied in combination of outstanding numerical and problem solving abilities, being a strong competitive advantage of males often non-achieved by females.

Thus, better earning profile of men, in spite of their lower formal education attainments, may originate not only from the believed higher self-confidence in bidding a wage (Card et al. 2015), compared to women, but also from higher numeracy and problem solving skills combined, which were usually not controlled for in analysis due to a lack of empirical evidence regarding individual competencies.

Another fundamental question addressed in our research was to investigate the labour market returns to unique human capital across genders. The results showed that earnings of "out-of-common-support" men and women generally exceed wage outcomes of males and females with comparable set of characteristics. Thus, individuals holding unique for their gender characteristics over-perform males and females with comparable profiles, resulting in the higher wage outcomes.

However, the in-depth analysis of wage differential between unique males and females revealed that, despite positive wage returns to gender-unique characteristics for both women and men, latter are still earning more and what is of particular importance, gender gap is more uneven along the wage distribution in the unique sub-samples, compared to sub-samples of men and women having comparable characteristics. Namely, our results showed even larger "glass ceiling" effect<sup>14</sup> for females with characteristics not observed among males, compared to those "matched" to males in terms of their profiles. It provides additional evidence to the pay gap analysis, suggesting that female-unique characteristics are less valuable at a labour market, relative to male-unique, leading to a naturally higher wage returns of men. In the traditional Oaxaca-Blinder parametric set up, this effect was captured by unexplained fraction of a total wage differential, leading to overestimation of gender discrimination on a labour market.

The further analysis of individual skills' effects on wage within male and female unique profiles revealed that earnings are contingent on these unique qualities differently for men and women. Men's higher numeracy scores are associated with the largest wage increase among low-earners, while women in the lower end of wage distribution benefit similarly from the higher literacy score. The role of problem solving competence increases along wage distribution and the largest benefit is observed in the highest wage rates for both males and females having characteristics non-matched with the opposite gender.

All in all, the novel perspective towards gender disparities in human capital and introducing a concept of gender-unique human capital within the wage gap framework, proved that men's and women's profiles cannot be directly compared, as particular characteristics are exclusive for certain gender. Ignoring this notion leads to overestimation of discriminatory labour market effects and thus imprecise wage inequality estimation. An important question for further research is to analyze men's and women's non-cognitive abilities formation in order to elaborate better understanding of dramatic differences in exploiting male and female skills on a labour market.

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<sup>14</sup> Extensively studied by Albrecht et al. (2003) and (2009), Xiu and Gunderson (2012).

Investigation of the underlying reasons behind superior skill attainments of men despite their lower formal education will enable to detect why women's "brain drain" happens, being of particular policy value.

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## Appendix 1

Descriptive statistics of the total sample of the full-time employed respondents, by gender

Variable	Female	Male
<i>Socio-Demographic Characteristics</i>		
Average age, years	43.2	40.5
Immigrant in 1st generation, %	10.52	9.66
Living with a partner, %	75.66	84.41
Kids (1=yes)	0.8	0.73
Health condition (1=excellent, 5=very poor)	3.01	2.97
<i>Education</i>		
Higher	51.19	34.67
Secondary	41.41	51.38
Lower	7.4	13.95
<i>Average skill levels, points</i>		
Literacy	279.4	278.6
Numeracy	273.2	280.4
Problem solving	270.7	276.3
<i>Employment-related characteristics</i>		
Average work experience, years	21.1	19.7
Occupation, %		
Skilled occupations	51.67	37.08
Semi-skilled white-collar occupations	27.03	9.1
Semi-skilled blue-collar occupations	12.19	48.31
Elementary occupations	9.11	5.51
Employed in private sector, %	58.92	79.68
Industry of employment, %		
Primary	2.70	6.38
Manufacturing	17.19	25.92
Energy	0.85	2.89
Construction	1.22	15.33
Sales and trade	16.13	9.34
Transport	2.64	10.59
Business services	15.44	10.72
Information and financial services	4.87	4.67
Public administration	9.89	7.76
Education	18.77	4.41
<b>Average wage, EUR</b>	<b>747</b>	<b>1186</b>
<b>Number of observations</b>	<b>1891</b>	<b>1520</b>

## Appendix 2

Non-parametric (Ñopo) decomposition of gender pay gap under alternative model specifications

Model specification	Wage gap decomposition estimates					Matched women		Matched men	
	$\Delta$	$\Delta_O$	$\Delta_X$	$\Delta_F$	$\Delta_M$	%	N	%	N
1. Age, education	0.5888	0.6417	-0.0470	0.0015	-0.0074	99.37	1879	97.11	1476
2. Age, education, immigrant status	0.5888	0.6348	-0.0451	-0.0085	-0.0085	97.25	1820	95.46	1432
3. Age, education, health	0.5888	0.6350	-0.0398	0.0059	-0.0123	90.27	1707	90.92	1382
4. Age, education, marital status	0.5888	0.6323	-0.0314	0.0010	-0.0131	90.96	1501	96.45	1319
5. Age, education, health, immigrant and marital status	0.5888	0.6157	-0.0157	0.0215	-0.0326	72.82	1157	81.71	1095
6. Age, education, work experience	0.5888	0.6135	-0.0293	0.0049	-0.0003	94.13	1778	92.76	1407
7. Age, education, work experience, occupation	0.5888	0.6191	-0.0576	0.0790	-0.0516	71.02	1337	74.93	1121
8. Age, education, work experience, industry	0.5888	0.4823	0.0069	0.0149	0.0848	51.61	974	51.38	778
9. Age, education, work experience, literacy	0.5888	0.5900	-0.0149	0.0148	-0.0011	78.64	1485	78.62	1192
10. Age, education, work experience, numeracy	0.5888	0.5900	-0.0271	0.0193	0.0193	76.89	1452	76.45	1159
11. Age, education, work experience, problem solving	0.5888	0.5547	-0.0234	0.0029	0.0547	79.01	1016	82.83	838
12. Age, education, work experience, literacy and numeracy	0.5888	0.5508	0.0230	0.0171	-0.0020	56.74	1071	59.47	901
13. Age, education, work experience, literacy and problem solving	0.5888	0.5507	-0.0238	-0.0173	0.0792	63.35	720	67.83	610
14. Age, education, work experience, numeracy and problem solving	0.5888	0.5888	-0.0224	-0.0321	0.0960	62.14	697	66.38	588
15. Age, education, work experience, all skills	0.5888	0.5458	-0.0177	-0.0702	0.1309	49.55	459	53.68	395
16. Age, education, work experience, industry, literacy	0.5888	0.4495	0.0077	0.0064	0.1252	25.12	473	26.32	397
17. Age, education, work experience, industry, numeracy	0.5888	0.4739	0.0386	0.0030	0.0733	24.06	453	26.25	396
18. Age, education, work experience, industry, problem solving	0.5888	0.5046	-0.0037	-0.1189	0.2069	41.25	302	46.25	282
19. Age, education, work experience, industry, literacy and numeracy	0.5888	0.4571	0.0187	-0.0122	0.1252	14.33	232	15.46	269
20. Age, education, work experience, industry, literacy and problem solving	0.5888	0.5241	-0.0061	-0.1773	0.2482	33.58	157	36.97	141
21. Age, education, work experience, industry, numeracy and problem solving	0.5888	0.5028	-0.0055	-0.1732	0.2648	33.69	159	36.97	141
22. Age, education, work experience, industry, all skills	0.5888	0.5142	-0.0060	-0.2098	0.2903	30.14	92	33.09	82

Note: Dependent variable is log monthly earnings of full-time employed

## Appendix 2 (continuation)

Parametric (Oaxaca-Blinder) decomposition of gender pay gap under alternative model specifications

Model specification	Wage gap estimates			N
	Total	Explained	Unexplained	
1. Age, education	0.5888	-0.0528	0.6416	3411
2. Age, education, immigrant status	0.5937	-0.0543	0.6481	3373
3. Age, education, health	0.5883	-0.0577	0.6460	3410
4. Age, education, marital status	0.6051	-0.0506	0.6557	3045
5. Age, education, health, immigrant and marital status	0.6045	-0.0494	0.6538	3044
6. Age, education, work experience	0.5890	-0.0424	0.6314	3406
7. Age, education, work experience, occupation	0.5900	-0.0123	0.6023	3387
8. Age, education, work experience, industry	0.5890	0.0643	0.5247	3406
9. Age, education, work experience, literacy	0.5890	-0.0341	0.6232	3406
10. Age, education, work experience, numeracy	0.5890	-0.0065	0.5955	3406
11. Age, education, work experience, problem solving	0.5810	-0.0198	0.6008	2512
12. Age, education, work experience, literacy and numeracy	0.5890	-0.0058	0.5890	3406
13. Age, education, work experience, literacy and problem solving	0.5810	-0.0183	0.5993	2512
14. Age, education, work experience, numeracy and problem solving	0.5810	-0.0022	0.5832	2512
15. Age, education, work experience, all skills	0.5810	-0.0025	0.5835	2512
16. Age, education, work experience, industry, literacy	0.5890	0.0807	0.5084	3406
17. Age, education, work experience, industry, numeracy	0.5890	0.1087	0.4803	3406
18. Age, education, work experience, industry, problem solving	0.5810	0.0805	0.5006	2512
19. Age, education, work experience, industry, literacy and numeracy	0.5890	0.1089	0.4801	3406
20. Age, education, work experience, industry, literacy and problem solving	0.5810	0.0842	0.4968	2512
21. Age, education, work experience, industry, numeracy and problem solving	0.5810	0.5810	0.4823	2512
22. Age, education, work experience, industry, all skills	0.5810	0.0974	0.4836	2512

Note: Dependent variable is log monthly earnings of full-time employed



### Appendix 3

Descriptive statistics for unique human capital by gender and under different matching specifications

Variable	Base model <sup>1</sup>		Base model + work experience <sup>2</sup>		Base model + occupation <sup>3</sup>		Base model + industry <sup>4</sup>	
	Female	Male	Female	Male	Female	Male	Female	Male
Average age, years	43	38	43	38	42	38	42	38
Immigrant in 1st generation, %	12.4	11.1	11.7	10.6	12.2	10.4	10.3	9.1
Educational level, %								
- Higher education	59.3	33.2	58.4	36.2	53.6	31.7	58.9	38.3
- Secondary education	33.8	49.1	35.7	49.6	39.9	53.5	35.5	49.1
- Basic education	6.9	17.6	6.0	14.3	6.6	31.7	5.6	12.6
Average skill levels, points								
- Literacy	271	278	275	279	274	278	278	281
- Numeracy	268	286	272	287	271	285	276	288
- Problem solving	262	272	265	273	264	271	269	275
Average work experience, years			20	18				
Occupation, %								
- Skilled occupations					52.4	37.1		
- Semi-skilled white-collar occupations					32.1	10.3		
- Semi-skilled blue-collar occupations					8.7	47.8		
- Elementary occupations					6.8	4.8		
Industry of employment, %								
- Primary							2.4	5.6
- Manufacturing							14.0	24.5
- Energy							1.0	3.7
- Construction							1.4	15.4
- Sales and trade							15.5	9.6
- Transport							3.0	10.4
- Business services							14.8	10.4
- Information and fin. serv.							6.2	6.1
- Public administration							11.4	8.3
- Education							19.0	4.3
Average wage, EUR	787	1282	797	1291	773	1263	816	1301
<b>Number of observations</b>	<b>799</b>	<b>584</b>	<b>1074</b>	<b>791</b>	<b>1034</b>	<b>795</b>	<b>1252</b>	<b>949</b>

<sup>1</sup> “Out-of-common-support” gender-specific samples defined based on matching model referred to in Section 4 (males and females matched on age, immigrant status, formal education attained and cognitive skills in three domains)

<sup>2, 3, 4</sup> Females and males matched additionally to base variables on work experience, occupation and industry respectively

#### Appendix 4

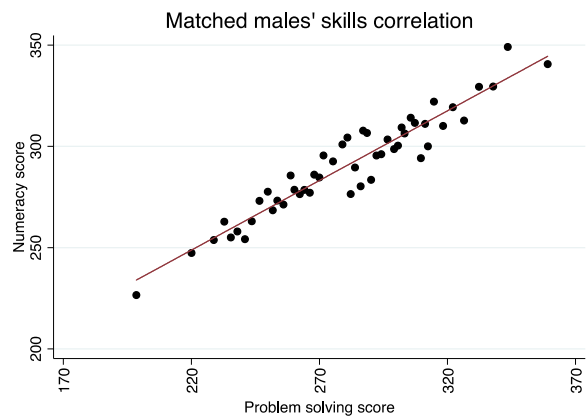
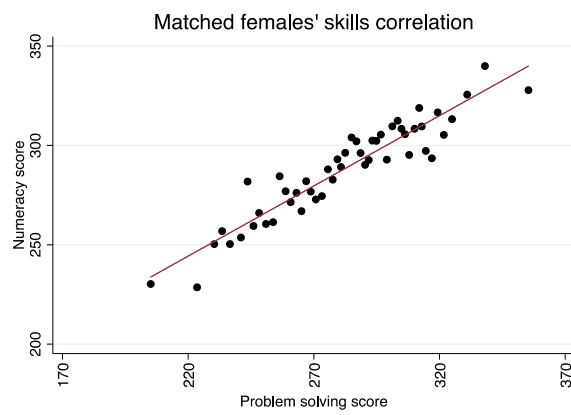
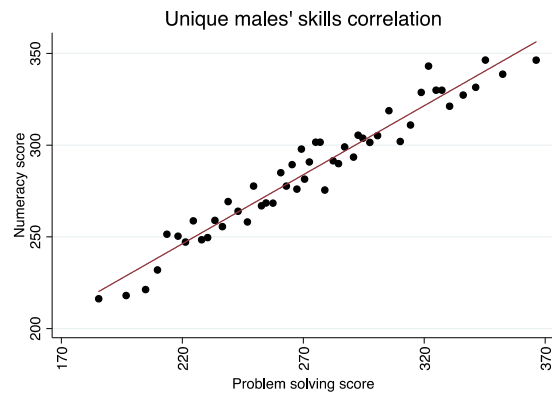
Two-sample Kolmogorov-Smirnov test results for the distribution of men's and women's skills

Skill domain <sup>1</sup>	Unique sample		Matched sample	
	Difference	p-value	Difference	p-value
Literacy	0.1147	0.000	0.0752	0.084
Numeracy	0.1788	0.000	0.0782	0.064
Problem solving	0.1016	0.002	0.0384	0.802

<sup>1</sup> Categorical variables of skills are considered (below 176, 176-226, 227-276, 277-326, 327-376, above 376 points).

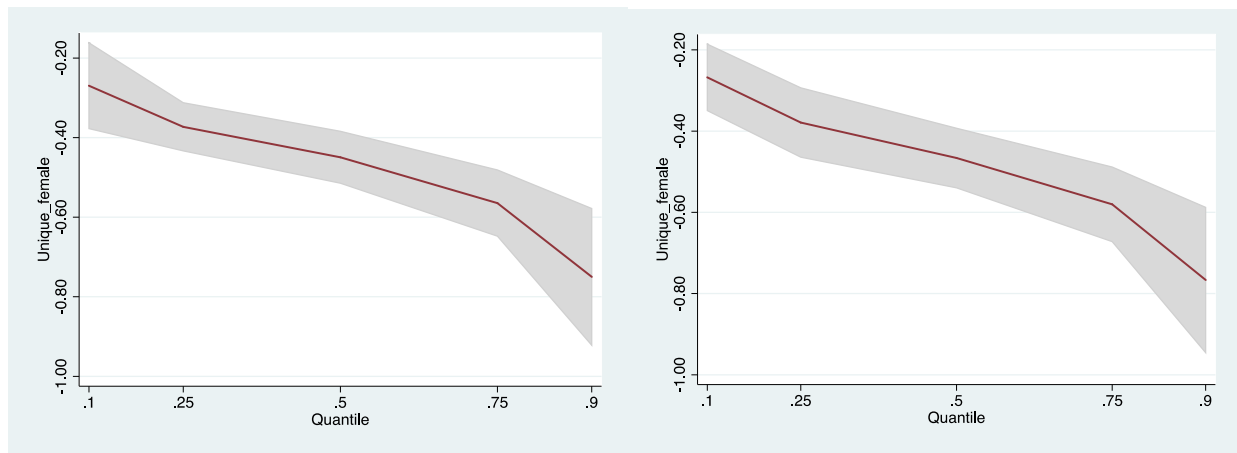
## Appendix 5

Numeracy-problem solving skills correlation by gender in unique and matched samples (binned scatter plot)



## Appendix 6

Female quantile regression coefficients for the unique sample including observations with self-derived earnings (left) and excluding those (right)



### Appendix 6 (continuation)

Female coefficients in usual OLS and quantile wage regressions (excluding respondents with derived earnings)

Female wage gap	OLS <sup>1</sup>	Quantile regression					N
		10th	25th	50th	75th	90th	
"Unique" sample	-0.470 (.0230)***	-0.268 (.0584)***	-0.379 (.0288)***	-0.466 (.0312)***	-0.580 (.0265)***	-0.767 (.0661)***	1346
"Matched" sample	-0.444 (.0300)***	-0.399 (.0545)***	-0.379 (.0296)***	-0.442 (.0354)***	-0.501 (.0352)***	-0.514 (.0789)***	1076

<sup>1</sup> OLS survey regressions with standard errors estimated using Jackknife replication methodology

Note: The sample includes only respondents with self-reported earnings. Dependent variable is log monthly earnings of full-time employees. The models additionally controls for age, age squared, first generation immigrant status, formal education attained, literacy, numeracy and problem solving scores. \*\*\*, \*\*, \* Indicate parameters significant at 1%, 5% and 10% levels respectively.