Gender wage gap trends in Europe: The role of occupational skill prices*

Ezgi Kaya†

Cardiff Business School, Cardiff University

Abstract

This paper explores gender wage gap trends by assessing the role of changing wage returns to occupational skills, brains—cognitive and interpersonal skills, and brawn—motor-skills and physical strength. Using harmonised data for six European countries and comparable data for the US, this paper finds substantial variation in the impact of occupational skill prices across countries. However, in all countries, a considerable portion of the change in the gender wage gap cannot be explained by changes in occupational skill prices.

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† Address: Cardiff Business School, Cardiff University, Aberconway Building, Colum Drive, Cardiff, CF10 3EU, UK E-mail: KayaE@cardiff.ac.uk. The author would like to thank the editor and two anonymous reviewers for their valuable comments that greatly improved this paper. The author is grateful to Nezih Guner and Ana Rute Cardoso for their valuable advice. Many thanks to Manuel Arellano, Francine Blau, David Card, Michael Coelli, Juan J. Dolado, Francesco Fasani, Libertad González, Lawrence Kahn, Pedro Mira, Ana I. Moro-Egido, Pau Salvador Pujolás Fons, Virginia Sánchez Marcos and the participants in the Annual Conference of the European Society for Population Economics (ESPE) in Bath, the AIEL National Conference of Labour Economics in Napoli, the IAFFE Annual Conference in Barcelona, the COSME-FEDEA Annual Workshop on Gender Economics in Madrid, the ENTER Jamboree in Barcelona, and the seminar participants at the Universitat Autònoma de Barcelona. Financial support by the Spanish Ministry of Science and Innovation through grant Consolidated Group-C ECO2008-04756 and FEDER is gratefully acknowledged.

1. Introduction

There was a dramatic decline in the gender wage gap in the US during the 1980s. The fact that this happened despite a significant increase in overall wage inequality has shifted attention in the literature to the relationship between the overall wage structure and the gender wage gap. The key change in the US wage structure in the 1980s were the rising returns to education and work experience due to an increase in the demand for high-skilled labour (Juhn, Murphy and Pierce 1993; Katz and Murphy 1992). In their seminal paper, Blau and Kahn (1997) show that the change in the US wage structure should have widened the gender wage gap since women had an initial relative deficit in these labour market characteristics such as education and work experience. However, women were able to overcome this deficit by improving their relative qualifications, especially their work experience and occupational allocation.

The existing literature attributes the increase in the relative demand for high-skilled labour to technological change, in particular to developments in computer technology (Katz and Autor 1999). The task-based approach of skill-biased technological change proposed by Autor, Levy and Murnane (2003), and further developed by Acemoglu and Autor (2011), Autor and Handel (2013), Goos, Manning and Salomons (2014), moves beyond traditional measures of labour market characteristics to model the relationship between skills and technological change through tasks performed in occupations. In this framework, tasks performed in an occupation are classified as routine and non-routine, which are substitutes for and complements to computers, respectively. With the development of computer technologies, a shift in production technology occurred in favour of more skilled workers, who perform non-routine job tasks, relative to less skilled workers, who perform routine job tasks.

How can the task-based approach of skill-biased technological change explain the changes in the overall wage structure and in the gender wage gap? To address this question, Welch (2000) considers labour as consisting of only two primary attributes: brains, i.e. cognitive and interpersonal skills; and brawn, i.e. motor skills and physical strength. Brains are assumed to be complementary to computer technologies. Welch (2000) argues that if women are relatively more intensive in terms of brains and/or men are relatively more brawn-intensive, then technological progress would increase the relative value of brains, leading to an increase in the wages of women relative to men.[1] Moreover, an increase in the value of brains relative to brawn would also increase the relative wages of men in brain intensive occupations compared to men in less brain intensive occupations, leading to an increase in male wage inequality. Therefore, both the decline in the gender wage gap and the increase in wage inequality can be attributed to changes in the relative prices of occupational skills. In fact, focusing on the different aspects of occupational skills, Bacolod and Blum (2010) show that the increase in the value of cognitive and people skills relative to manual skills and physical strength between 1968 and 1990 accounted for 20 per cent of the narrowing gender wage gap and up to 40 per cent of rising wage inequality in the US.

In this paper, we revisit the findings of Bacolod and Blum (2010) for six European countries (Austria, Ireland, Italy, Portugal, Spain, and the UK) and the US. To characterise occupational skills (brains and brawn), we utilise Occupational Information Network (O*NET) data. The individual-level data on wages and worker characteristics come from various surveys, including the first wave of the European Community Household Panel (ECHP) in 1994 – except for Austria, for which we use the 1995 wave, as it had joined the

[1] Consistent with this argument, Ngai and Petrongolo (2017) propose a model for production of goods in the market and services (produced both in the market and at home) in which women have a comparative advantage in producing services that are relatively less brawn- and more brain-intensive than the production of goods, and argue that the historical growth in the service sector has created jobs for which women have a natural comparative advantage. The evidence also suggests that women value jobs that are relatively more people skill intensive and less brawn intensive (Lordan and Pischke 2016) and that people skills play a role in predicting labour market outcomes (see, for example, Almlund et al. 2011; Borghans et al. 2008, 2014).

survey by then, the 2008 wave of the European Union Statistics on Income and Living Conditions (EU-SILC), and the Current Population Survey (CPS) March Supplements in 1995 and 2009.[2] The pay information in the ECHP, EU-SILC and CPS for years 1994 (except for Austria 1995) and 2008 enables us to estimate the returns to brains and brawn in each country conditional on traditional human capital variables (education and work experience) for the two time points. We then quantify the contribution of changes in occupational skill prices by decomposing the change in the gender wage gap for each country between the two years into its components using a technique developed by Juhn, Murphy and Pierce (1991).

Our results show that in the US, from 1994 to 2008, brains became relatively more valuable than brawn. As a result, part of the narrowing of the US gender wage gap (around 20 per cent) can be explained by the change in occupational skill prices. During the same period, the gender wage gap also narrowed in our sample of European countries, except in Spain. Similar to the US experience, in the UK and Austria, part of the narrowing gender wage gap can be explained by changes in returns to brains and brawn. In particular, changes in relative skill prices accounted for around seven per cent and 20 per cent of the narrowing gender wage gap in the UK and Austria, respectively. However, the increase in returns to brains and the decrease in returns to brawn were not a common phenomenon for the sample of European countries. In contrast to the US experience, in Southern European countries, including Italy, Portugal and Spain, and in Ireland, the changes in returns to brains and brawn skills had a widening effect on the gender wage gap.

[2] Throughout the paper, we refer to the years of the income reference period rather than the survey years. In the ECHP and EU-SILC, we have information on earnings and work-related characteristics for the current period. In the CPS March Supplements, we use information on earnings and work-related characteristics for the previous year (see, for further details, Data Appendix).

Given the vast literature related to the narrowing of the gender wage gap (see, for recent surveys, Blau and Kahn 2017; Goldin 2014; Kunze 2018), relatively few studies have focused on the skill requirements of occupations to analyse gender wage gap trends in European labour markets, presumably driven by a lack of comparable data.[3] This paper sought to fill this gap in the literature. One paper that is particularly relevant to the current study is Bacolod and Blum (2010), which investigates how changes in the relative prices of cognitive, motor and people skills, as well as physical strength, have affected the gender wage gap in the US. Bacolod and Blum (2010) show that from 1968 to 1990, cognitive and people skills became relatively more valuable compared to motor skills and physical strength. During the same period, since females held occupations that required more cognitive and people skills relative to males, changes in relative skill prices narrowed the gender wage gap. In our analysis, we show that the previous patterns of relative skill prices observed in the US between 1968 and 1990 persisted into the period from 1994 to 2008. Furthermore, we also explore the effect of changing skill prices on gender wage gap trends for a set of European countries.

Our results correspond to those of Black and Spitz-Oener (2010) and Borghans, Ter Weel and Weinberg (2014). Using self-reported measures of tasks performed within occupations, Black and Spitz-Oener (2010) employ a task-based approach to study the effect of changing tasks on gender wage gap trends in Germany from 1979 to 1999. Their results indicate that changes in relative tasks and relative prices together explain more than 40 per cent of the narrowing gender wage gap in West Germany despite the widening effect of changing task prices. Overall, these results parallel our findings as for Southern European countries and

[3] In a recent study, De La Rica, Gortazar and Lewandowski (2020) use data from the Programme for the International Assessment of Adult Competencies (PIAAC) to construct job tasks for a harmonised sample of developed countries. Their focus is, however, on the cross-sectional relationship between job tasks and wage, not on the gender pay gap.

Ireland, for which we find that the changes in relative skill prices had a mitigating effect on the convergence of wages of men and women. Differently, we characterise occupations by skill requirements instead of self-reported measures of routine or non-routine tasks. Using data for Germany, the US and the UK, Borghans, Ter Weel and Weinberg (2014) show that occupations that require more computer usage and a higher degree of teamwork require more people skills. Moreover, women have a relatively higher employment rate in occupations that require people skills. They suggest that the increased importance of people skills due to technological change and innovative work practices has increased women's relative employment in these occupations. Our results complement their findings by exploring the role of changes in relative skill prices on the gender wage gap in various countries including the UK and the US.

The remainder of the paper is organised as follows. The next section explains the details of the decomposition technique employed. The third section describes our data sources, samples and variables, followed by descriptive statistics. The fourth section investigates the change in occupational skill prices. The main results for the decomposition of the change in the gender wage gap are presented in the fifth section. Finally, section six concludes.

2. Analytical framework

In our analysis, we use a framework developed by Juhn, Murphy and Pierce (1991) which has been widely used in the gender wage gap literature to explore over time (see, for example, Blau and Kahn 1997) and cross-country differences (see, for example, Blau and Kahn 1996, 2003). This framework extends the standard Oaxaca-Blinder (1973) method of decomposing wage differentials at one point in time, to decompose changes over time by parcelling out the changes in the gender pay gap into four components: (i) changes in the observed characteristics of women compared to men; (ii) changes in the prices of observed characteristics; (iii) changes in the prices of unobserved characteristics (or residual wage inequality); and (iv) changes in the unexplained gap (corrected for the impact of changes in the prices of unobserved characteristics). Formally, suppose that we have for each male i at time t the following wage equation:

$$\ln W_{it} = X_{it}\beta_t + S_{it}\gamma_t + \sigma_t\theta_{it} \quad (1)$$

where $\ln W_{it}$ is the natural logarithm of gross hourly wage, X_{it} is a set of explanatory variables (such as education and work experience), β_t is the vector of prices of these variables, S_{it} is a set of occupational skills (such as brains and brawn) and γ_t is the vector of prices of these skills. In equation (1), the component of wages accounted for by unobservable characteristics is expressed in terms of the standardised residual θ_{it} (with zero mean and unit variance), and a residual standard deviation of σ_t (the degree of the residual wage inequality for males). Once the ordinary least squares (OLS) estimates for the male's price vectors $\hat{\beta}_t$ and $\hat{\gamma}_t$ and the residual standard deviation $\hat{\sigma}_t$ are obtained, the gender wage gap at time t can be decomposed as follows:

$$\Delta \ln W_t \equiv \overline{lnW_t}^M - \overline{lnW_t}^F = \left[\Delta\overline{X_t}\hat{\beta}_t + \Delta\overline{S}_t\hat{\gamma}_t\right] + \hat{\sigma}_t\Delta\overline{\theta}_t, \quad (2)$$

where the M and F superscripts denotes males and females, respectively; an over-bar represents the value of the sample average of the corresponding variable; and a prefix signifies the average male-female difference for the immediately following variable. Using the price vectors for males from equation (1) relies on the assumption that the prices derived from the male wage regression are equivalent to competitive prices. Since male-female differences in returns can also reflect discrimination, the male equation is employed to simulate the wage equation in a non-discriminatory labour market (Blau and Kahn 2017). Moreover, using male prices ameliorates potential problems due to non-random selection since male employment rates are quite stable over time (Blau and Kahn 1997; Kunze 2008).[4]

Based on the decomposition equation for a single period (equation (2)), the change in the gender wage gap from period t to t' can be decomposed as follows:

$$\begin{aligned}
\underbrace{\Delta \ln W_{t'} - \Delta \ln W_t}_{\text{change in observed gender wage gap}} &= \underbrace{\overbrace{(\Delta\bar{X}_{t'} - \Delta\bar{X}_t)\hat{\beta}_{t'}}^{\text{observed } X'\text{s effect}} + \overbrace{(\Delta\bar{S}_{t'} - \Delta\bar{S}_t)\hat{\gamma}_{t'}}^{\text{observed } S'\text{s effect}}}_{\text{observed characteristics effect}} \\
&+ \underbrace{\overbrace{\Delta\bar{X}_t(\hat{\beta}_{t'} - \hat{\beta}_t)}^{\text{observed } X \text{ prices effect}} + \overbrace{\Delta\bar{S}_t(\hat{\gamma}_{t'} - \hat{\gamma}_t)}^{\text{observed } S \text{ prices effect}}}_{\text{observed prices effect}} \\
&+ \underbrace{(\Delta\bar{\theta}_{t'} - \Delta\bar{\theta}_t)\hat{\sigma}_{t'}}_{\text{gap effect}} \\
&+ \underbrace{\Delta\bar{\theta}_t(\hat{\sigma}_{t'} - \hat{\sigma}_t).}_{\text{unobserved prices effect}} \qquad (3)
\end{aligned}$$

In equation (3), the first term is the ‘observed characteristics effect’, which measures the impact of the change in gender differences on education and work experience (‘observed X’s effect’) and occupational skills (‘observed S’s effect’). The second term, the ‘observed prices effect’, measures the effect of changes in (male) returns to education and work experience (‘observed X prices effect’) and skill prices (‘observed S prices effect’). The third term, the ‘gap effect’, captures the impact of changes in differences in unobserved variables for men

[4] It is also worth noting that the first term on the right-hand side of equation (2) corresponds to the portion of the gap attributable to differences in the observed characteristics and skills between men and women, valued at male prices, and coincides with the explained component of the standard Oaxaca–Blinder decomposition. On the other hand, the unexplained component of the Oaxaca–Blinder decomposition represents the difference in wage an average woman would have received at the male returns and her actual wages. In equation (2) this is interpreted in terms of the (minus) mean value of the (hypothetical) female residuals, that are derived by taking the difference between actual female hourly wages and the hourly wage each female would receive if rewarded according to the male wage equation.

and women. That is, it measures the effect of changing differences in the percentile ranking of men and women in the male residual wage distribution after controlling for education, experience and occupational skills and holding the degree of residual male wage inequality constant. The final term, the 'unobserved prices effect', measures the impact of a change in male residual inequality on gender wage gap trends, assuming that females maintain the same percentile ranking in the residual wage distribution of men. In other words, it shows the contribution of changes in the returns to unobservable qualifications and skills to the change in the gender wage gap.[5]

To perform the decomposition analysis, we start by estimating the male wage equation for each country in our sample for each year. Then, we predict what wage each woman would have had if she were paid according to the estimated male wage equation. The first two components, the 'observed characteristics effect' and the 'observed prices effect', are straightforward to calculate using the estimated coefficients and sample means by gender. A change in the unexplained component of the gender wage gap is given by the sum of 'gap effect' and 'unobserved prices effect'. Following Juhn, Murphy and Pierce (1991), we estimate these terms by adapting a non-parametric approach that uses the entire distribution of male and female residuals from the male wage equation for both time points. In particular, the 'gap effect' is obtained by assigning each woman at time t' a percentile number corresponding to her position in the male wage residual distribution of time t'. We then use these relative ranks to derive the hypothetical residuals at time t. The average of female hypothetical wage residuals is our estimate of $(-\Delta\bar{\theta}_t\hat{\sigma}_{t'})$. The actual average female wage residual from the male distribution of residuals at time t' constitutes our estimate of

[5] In our analysis, we perform decomposition using workers in all education groups controlling for education dummies and labour market experience. Hence, our estimates capture the effects of occupational skill prices on residual inequality.

$(-\Delta\bar{\theta}_{t'}\hat{\sigma}_{t'})$. The difference between the average of the imputed wage residuals at time t and the average residual at time t' is used to compute the 'gap effect', $(\Delta\bar{\theta}_{t'} - \Delta\bar{\theta}_{t})\hat{\sigma}_{t'}$. The 'unobserved prices effect' is computed as the difference $\Delta\bar{\theta}_{t}(\hat{\sigma}_{t'} - \hat{\sigma}_{t})$ holding the percentile location corresponding to each woman's position at time t fixed.

It is worth nothing that the Juhn, Murphy and Pierce decomposition method has not been free of criticism (see, for example, Suen 1997; Yun 2008). In particular, the decomposition results may be misleading if the standard deviation of male wage residuals used in computing the 'unobserved prices effect' and the percentile ranking used in the 'gap effect' calculations are dependent. As such, an increase in male wage inequality would mechanically increase the mean female residual percentile. Then, one would expect a greater increase in the female percentile ranking in countries where the increase in male wage inequality was greater. While this is a valid concern, our decomposition results do not indicate such a pattern across countries (see Section 5).

3. Data

Our occupational skill data come from the O*NET database, which was developed by the US Department of Labour and is the most well-known source for information on occupations in the US labour market. This database is a replacement for the Dictionary of Occupational Titles (DOT), which has been extensively used in earlier research (see, for example, Autor, Levy and Murnane 2003; Bacolod and Blum 2010; Goos and Manning 2007). Recently, the O*NET database has been used by several researchers to determine occupational skill requirements and the task content of occupations for European countries (see, for example, Amuedo and De la Rica 2011; Goos, Manning and Salomons 2009, 2014; Ortega and Polavieja 2012).

We use version 15.0 of the O*NET database (released in June 2010), which provides detailed information about worker and job characteristics for more than a thousand occupations. To map O*NET codes to the occupation codes used in our individual data sources, we utilised two different crosswalks provided by the Centre for Longitudinal Studies and Integrated Public Use Microdata Samples (IPUMS). However, as with most surveys, our individual-level datasets do not code to such a detailed occupational classification. Therefore, we map several O*NET occupations to a small number of occupation categories by calculating a weighted average across the component O*NET occupations, where the weights correspond to 2001 US employment data reported by the Bureau of Labor Statistics (2010) (see, for further details, Data Appendix).

Next, we use textual definitions of the O*NET variables to identify two broad occupational skill categories: brains and brawn. The 52 different variables of worker abilities available in the O*NET fall into five clusters: cognitive abilities; psychomotor abilities; endurance; flexibility, balance and coordination; and sensory abilities. O*NET also includes a cluster of social skills under worker requirements which provides six different variables measuring developed capacities used to work with people to achieve goals. To construct brains, we use all the variables classified under cognitive abilities and social skills, while all the variables classified under psychomotor abilities; endurance; and flexibility, balance and coordination are used to construct brawn (see Appendix Table A1).[6] To facilitate the interpretation of our findings, we transform the O*NET variable scores by using the minimum and the maximum score of the variable in question in other occupations. As such, each final O*NET variable score ranges between zero and one and is indicative of the relative importance of that ability

[6] Excluded worker ability descriptors largely pertaining to sensory dimensions that influence visual, auditory and speech perception, as they are not clearly classified under one of the two sets according to their textual definitions.

in the occupation in question as opposed to its importance in other occupations.[7] Finally, using the rescaled values, we construct the measures of brains and brawn by taking the simple average of a corresponding set of variables. We present the skill content of occupations using the constructed measures of brains and brawn in Appendix Table A2. Intuitively, at the top of the brain-intensive jobs are professionals, managers, legislators, and senior officials, while at the top of the brawn-intensive jobs are labourers and elementary occupations.

As there is currently no single data source available to study the long-term dynamics of the wage structure, the individual-level data on wages and worker characteristics come from various sources. For European countries, data on worker characteristics and wages come from the ECHP and its successor EU-SILC. Countries included in our analysis are Austria, Ireland, Italy, Spain, Portugal and the UK.[8] For the US, the individual-level data come from the CPS March Supplements provided by IPUMS (Flood et al. 2020). In our analysis, we use the first wave of the ECHP in 1994 – except for Austria, for which we use the 1995 wave, as it had joined the survey by then. We supplement the ECHP data with the 2008 EU-SILC data. As the CPS March Supplement uses the previous calendar year as the income reference period,

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[7] Formally, let s_{kj} be the value of O*NET variable k for occupation j, where $j = 1,2, \ldots 18$; and its maximum and minimum values among occupations be $\overline{s_k}$ and $\underline{s_k}$. Each skill descriptor value is rescaled as follows: $s_{kj}^* = (s_{kj} - \underline{s_k})/(\overline{s_k} - \underline{s_k})$.

[8] EU-SILC includes several measures of employee earnings; however, *current* gross monthly earnings are only reported for a set of countries (Austria, Greece, Ireland, Italy, Portugal, Spain and the UK). Gross earnings that relate to the year previous cover a much wider set of countries, however the other individual variables refer to the current period. This temporal mismatch provides a potential source of measurement error for covariates that can change over time, such as occupation. As a result, *current* gross hourly earnings, often the focus of studies of pay inequality can only be derived for Austria, Greece, Ireland, Italy, Portugal, Spain and the UK (see, for a similar discussion, Naticchioni, Ragusa and Massari 2014). Greece is omitted from our analysis owing to the smaller sub-samples with usable information.

we use information on earnings and work-related characteristics for the previous year using data from the 1995 and 2009 surveys (see Data Appendix).

We restrict our sample to individuals of prime working age (25–54 years old) who work at least 15 hours per week with valid observations on all the variables used in the analysis.[9] Gross hourly wages from the ECHP and EU-SILC are constructed by using current gross monthly wages and the usual hours worked in the main job; whereas for the US, the annual gross wages are divided by the product of weeks worked and the total number of hours usually worked per week.[10] Nominal wages are converted using the Purchasing Power Parity exchange rates, deflated using the Consumer Price Index, and measured in 2005 prices. Wage outliers greater than five times the 99th percentile of the country-year wage distributions or less than half the fifth percentile are dropped from the sample. Throughout our analysis sample weights are applied so the estimates are representative of the respective population.

Assuming that workers are assigned to jobs in some sort of hedonic market clearing process, we infer worker skills from the occupations in which they are employed and merge the occupational skill requirements data from the O*NET with individual-level data from various sources. This approach follows that of Autor, Levy and Murnane (2003) which assumes that workers are allocated to occupations by their comparative advantage (Roy 1951) and that in a labour market equilibrium, workers are matched to jobs that require skills they

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[9] Consistent with the cross-country studies of the gender wage gap (see, for example, Blau and Kahn 1996; Olivetti and Petrongolo 2008), we focus on prime working age group to avoid problems associated with cross-country differences in education and retirement systems. The restriction of working at least 15 hours per week is necessary because of the nature of the ECHP, since it does not distinguish individuals regularly working less than 15 hours per week from those who are out of the labour force in the first two waves.

[10] Gross hourly wages from the CPS are constructed using the annual gross wages for the previous year, which are top-coded. Following the common practice (see, for example, Katz and Revenga 1993 and Juhn et al. 1993), the top-coded values of the annual gross wages are multiplied by the value 1.45.

possess. While these assumptions appear to be rather restrictive, the evidence suggests that worker self-selection into occupations takes a form that is consistent with comparative advantage (Autor and Handel 2013).[11] However, it is also worth noting that this approach ignores the within-occupation variation of skills, and as such they are imperfect measures for worker skills. Nevertheless, assigning occupational-level information to individuals may still provide a reasonable approximation (see, for example, Cassidy 2017).

We present the details of all variables and their means (by country and year) for our matched dataset in Appendix Table A3. Consistent with existing evidence, female workers on average earned less than males in all the countries in each year, indicating the persistence of an observed gender wage gap. From 1994 (1995 for Austria) to 2008, most of the countries in our sample experienced a decline in the observed gender wage gap, except Spain.[12] One obvious explanation for the decline in the gender wage gap are the improved labour market characteristics of women. In fact, between the two years, the increase in the proportion of women with a tertiary degree was greater than that of men, and women were improving their work experience, on average (see Appendix Table A3).[13] Furthermore, between the two years, employment across occupations changed, resulting in a change in the average brain and brawn skill intensities of males and females, which is presented in Appendix Table A4. In most

[11] Although we do not explore the mechanisms behind the gender-typed occupational sorting and take the occupational allocation of men and women as given, it is also worth noting that the occupational sorting of men and women might be a consequence of both rational choice and socialisation processes (see, for a discussion, Leuze and Strauß 2016).

[12] See European Industrial Relations Observatory report on the increase in the gender wage gap in Spain during the late 1990s (Sanz de Miguel 2010). Using data from the ECHP and EU-SILC, Guner, Kaya and Sánchez-Marcos (2014) also show that the Spanish gender wage gap increased 0.074 log points from 1994 to 2004.

[13] The only exception for the former is Spain, where the increase in the proportion of men with a tertiary degree was 10.56 percentage points, while the increase was only 8.04 percentage points for women.

countries in the sample, females and males in 2008 were more intensive in brains and/or less intensive in brawn compared to their counterparts in 1994 (1995 for Austria).[14]

4. Returns to brains and brawn

In this section, we present the estimation results for the (male) wage returns to brains and brawn for each country in each year specified in equation (1). The workers' work experience, experience squared and dummies for having a tertiary degree (high education) and having a high school degree (secondary education) are included in the vector of worker characteristics X_{it} along with a constant term. The vector S_{it} contains the O*NET characteristics required to perform the occupation in which the worker is employed and proxies the occupational skill requirements: brains and brawn. Characterising worker skills as brains and brawn, as opposed to using occupational dummies in the regression, allows us to determine the relative skill prices instead of the wage differentials across occupations.[15]

[Table 1 here]

Table 1 presents the estimates of the male wage equations. The coefficient estimates for education and work experience have the expected signs: the wage rate increases with education level and work experience. The negative coefficient of experience squared confirms the concavity of the experience-earning profiles. Turning our attention to occupational skills, in all countries in the sample, brains are positively and significantly valued, while (male) wage

[14] Exceptions include Portugal and Spain, where in 2008 males in the former and females in the latter were less brain skill intensive and more brawn incentive than their counterparts in 1994.

[15] As there is no market for skills, and brains and brawn cannot be sold separately, the coefficient estimates for brains and brawn from equation (1) are interpreted as the marginal contributions of brains (∂lnwage/∂brains) and brawn (∂lnwage/∂brawn) to the logarithm of gross hourly wages. Throughout the paper, we refer to these as wage returns to these skills, or simply skill prices.

returns to brawn are negative and small. From 1994 to 2008, (male) wage returns to brains increased in Italy, the UK and the US by 18 per cent, five per cent and 22 per cent, respectively. In the UK and the US, as opposed to brains, brawn became less valuable over time, with the (male) wage return decreasing by more than 30 per cent. However, the increase in (male) wage returns to brains and the corresponding decrease to brawn were not a common phenomenon for the other European countries in the sample. During the period of analysis, in Austria, despite a decline in (male) wage returns to both brains and brawn, the wage penalty for brawn increased (by 57 per cent) more than the decrease in the price of brains (by seven per cent), and hence brains became relatively more valuable than brawn. On the other hand, brains became less valuable in Ireland, Portugal and Spain and the (male) wage penalty for brawn declined in all Southern European countries as well as in Ireland. The decline in wage penalty to brawns was around 45 per cent in Ireland and Italy, 40 per cent in Portugal and around 26 per cent in Spain. While this result may be surprising at first, it is consistent with the changes in other supply and demand factors that occurred in these countries during the period of analysis. For instance, this is a period the Spanish labour market experienced an educational upgrade of the labour force and an increase in immigration flows, as well as a construction boom. Carrasco, Jimeno and Ortega (2015) show that between 1995 and 2002 in Spain, there was a decline in the skill premium and a growth in the demand for less-educated workers, which was driven by a boom in the construction sector. McGuinness et al. (2009) also show that, between 1994 and 2001 the construction boom in Ireland incorporated many previously unemployed and low-skilled men. During the 1990s, Italy also experienced demand changes associated with exports, which shifted employment towards firms producing unskilled, intensive goods (Manasse, Stanca and Turrini 2004). Similarly, Centeno and Novo (2014) argue that the Portuguese economy experienced a shortage of skills from 1984 to 1995, particularly after joining the European Community in 1986. However, between 1995 and

2009, demand increased for low-skill services together with a mild boom in construction and the polarisation of work, and the minimum wage benefited low-skill jobs (against intermediate-skill jobs).

To test the sensitivity of our estimates of the skill prices, we estimate further variants of the (male) wage equation specified in equation (1). As a first robustness check, we investigate whether the construction of the occupational skill measures affects our wage equation estimates. For this purpose, we use Principal Component Analysis (PCA), which is a variable reduction technique commonly used in the literature to construct measures from DOT and O*NET databases (see, for example, Autor, Levy and Murnane 2003; Bacolod and Blum 2010; Goos, Manning and Salomons 2009; Ortega and Polavieja 2012). Using occupational skill measures constructed through PCA (see Appendix B), we redetermine the brains and brawn intensities of jobs and estimate the empirical model specified in equation (1). A comparison of the returns to skills using the alternative measures with our benchmark estimates suggests that the construction process of occupational skill measures does not alter our results (see Appendix Table C1).[16]

One concern related to our specification might be the negative correlation between occupational skill measures (see Appendix Table A2), since this may result in multicollinearity when both brains and brawn are used in the wage equation simultaneously.[17]

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[16] The skill measures constructed through PCA are unit-free as the rescaled skill measures, but the scale of measurement is different. However, using skill measures constructed with this alternative method produces negligible changes in the estimated coefficients.

[17] Due to high correlation between them, it was not possible to use more disaggregated skill variables (i.e. cognitive abilities, people skills, motor skills and physical strength) simultaneously since multicollinearity makes precise estimation impossible. Nevertheless, in an alternative specification, we consider the wage models with cognitive abilities, people skills, motor skills and physical strength entering individually. These results are consistent with our main results and available upon request.

To address this concern, at the bottom of Table 1, we present the mean variance inflation factor (VIF) values for occupational skill variables for each regression as a collinearity diagnostic statistic. The VIF is based on the proportion of variance in each independent variable that is not related to the other independent variables in the model. Conventionally, values larger than 10 have been considered to indicate serious multicollinearity (Hair et al. 1995; Kennedy 1992). In Table 1, the mean VIF values for occupational skill variables in each regression are much lower than 10, indicating no collinearity. As a further robustness check, we also estimate an alternative wage equation that control for the ratio of brains to brawn instead of brains and brawn entering into the wage equation separately. In line with our benchmark estimates, in this case, the coefficient estimates of the brains to brawn ratio are positive and significant, implying a positive return of working in a relatively more brains-intensive occupation (see Appendix Table C2).

One final concern might be related to the sample selection introduced by the substantial increase in women's employment rates over time.[18] Selectivity bias correction (Heckman 1979) is a common approach employed in the literature to overcome this problem, but we do not employ it in our benchmark estimates. The main reason for this is the identification problem pointed out by Neuman and Oaxaca (2004), which arises in the decomposition analysis with selectivity-corrected wage equations. Based on the objectives and assumptions, the selection component can be regarded in the overall decomposition in several ways, and it is not clear how to interpret the selection term (Neuman and Oaxaca 2004). Instead, we formulate the wage gap based on the male's wage equation. Since male-female differences in returns can also reflect discrimination, the use of the male's equation simulates the wage

[18] This is particularly observed in European countries in our sample with the increase in the employment-population ratio for prime age (25-54 years) women between the two time points examined varying from 4.7 percentage points for the UK to 25.4 percentage points for Spain (see Appendix Figure A1).

equation in a non-discriminatory labour market and ameliorates the problems due to non-random selection into work, since male employment rates are quite stable over time (Blau and Kahn 1997; Kunze 2008).

5. Decomposition of the changes in the gender wage gap

To explore the effect of changes in occupational skill prices on gender wage gap trends, we turn our attention to the decomposition results presented in Table 2. In Panel A, we first present a set of descriptive statistics on the wage distributions of males and females. The first two rows show the residual standard deviation for males from the (male) wage regression specified in equation (1). A higher residual standard deviation indicates higher wage inequality among males within education, experience, and skill (brains and brawn) levels. The evidence suggests that a compressed wage distribution disproportionately benefits women relative to men, and hence narrows the gender wage gap (Blau and Kahn 1996, 2003; Kahn 2015).[19] Rising wage inequality in the US in 1980s has been extensively studied in the literature (see, for example, Autor, Katz and Kearney 2008) and is found to work against a narrowing of the gender wage gap (Blau and Kahn, 1997). Cross-country studies also document a much greater wage inequality in the US compared to European countries, which is often attributed to the higher rewards of labour market skills due to the decentralised wage-setting mechanisms in the US (Blau and Kahn 1996; Katz and Autor 1999). Consistent with the earlier patterns, Table 2 indicates a higher degree of residual wage inequality in the US in 1994 than in any other European country. Moreover, from 1994 to 2008, the US male wage inequality increased. Similar to the US experience, Italy and the UK also experienced an

[19] The literature uses male (residual) wage inequality rather than overall wage inequality in measuring compression as there is a mechanical relationship between the latter and the gender wage gap (see, for a discussion, Kahn 2015).

increase in wage dispersion, while in Austria, Ireland, Portugal and Spain, the male residual wage inequality reduced.

We return to the role of changes in wage structure on the gender wage gap features more formally in what follows, but before, we turn our attention to the ‘mean female residual from the male wage regression’ and the ‘mean female residual percentile’, which are presented in the following four rows of the same panel. The former is usually interpreted as a measure of discrimination but might also capture the omitted productivity differences between males and females (Blau and Kahn 1997). As shown in Table 2, between the two years, most of the European countries in our sample (Portugal and Spain are the only exceptions) as well as the US experienced an increase in the ‘mean female residual percentile’ as well as in the absolute value of the female residuals, implying a progression of females within education, experience, and skill levels.

[Table 2 here]

The observed gender wage gap in 1994 (1995 for Austria) and 2008 and the change in the gap between the two years are presented in Panel B of Table 2. Consistent with the previous evidence for the 1980s (see, for example, Blau and Kahn 1996), the table indicates a significant variation in the initial gender wage gap across countries, with Austria, the UK and the US having the widest gaps. Ireland and Southern European countries rank towards the bottom of the group. With the exception of Spain, where the gender wage gap widened from 1994 to 2008 by 0.053 log points, the observed gender wage gap narrowed in all countries in our sample with the rate of narrowing varying substantially across countries (from 0.010 log points in Portugal to 0.133 log points in Ireland). Nevertheless, Austria, the UK and the US remain to be the highest ranked countries in 2008 in terms of their gender wage gap.

Can changes in wage returns to brains and brawn explain these trends? The following rows of Panel B aim to answer this question, where we present the components of the Juhn, Murphy and Pierce decomposition. From 1994 to 2008, around 20 per cent of the narrowing US gender wage gap can be explained by changes in wage returns to occupational skills (‘observed *S* prices effect’). Similar to the US experience, in Austria and the UK, part of the narrowing was due to changes in occupational skill prices. The portion of the narrowing gender wage gap that can be explained by the changes in (male) wage returns to brains and brawn is around 20 per cent in Austria and seven per cent in the UK. In contrast, the changes in returns to brains and brawn had a widening effect in Ireland, Italy, Portugal and Spain. The main reason for this is that, during this period in Southern European countries and in Ireland, the wage penalty for brawn, skills in which women had an initial deficit (see Appendix Table A4) reduced (see Table 1). In fact, in the absence of changes in skill prices, the gender wage gap would have narrowed even further in Ireland (to 0.116 log points instead of 0.100 log points), in Italy (to 0.022 log points instead of 0.046 log points) and Portugal (to 0.129 log points instead of 0.164 log points), while the Spanish gender wage gap would have widened (by around 0.040 log points instead of 0.053 log points).

The question, then, is what accounts for the gender wage gap trends. As presented in Table 2, in the US, changes in the observed labour market characteristics and prices (‘observed characteristics effect’ and ‘observed prices effect’) account for around 77 per cent of the narrowing in the gender wage gap. However, with the exception of Portugal and Spain, where the change in the gender wage gap between 1994 and 2008 can be fully explained by observable characteristics and prices, a substantial portion of the narrowing gender wage gap in other countries cannot be explained by observed factors. In fact, the narrowing gender wage gap in Ireland and Italy remains entirely unexplained by changes in observed characteristics and prices. In the UK, where changes in occupational skill prices have a similar effect to that in the US, the portion of the narrowing explained by changes in observed characteristics and prices is only 33 per cent. On the other hand, in Austria, where the change in occupational skill price changes account a similar portion of the narrowing gender wage gap to that in the US, the part of the change in the gender wage gap that is explained by observed factors conceals two offsetting effects. The sum of the change in observed prices of characteristics and occupational skills ('observed prices effect') accounts for about six per cent of the narrowing in the gender wage gap but this effect is offset by the change in observed characteristics ('observed characteristics effect') which acts to widen the gender wage gap. As a result, the narrowing gender wage gap in Austria remains entirely unexplained by changes in observed characteristics and prices.

Turning our attention to the remaining two components of the decomposition, the influence of 'unobserved prices effect' on the gender wage gap is narrowing in countries where the wage distribution was compressed between the two time periods (Austria, Ireland, Portugal and Spain (see Panel A)), while the effect is widening in Italy, the UK and the US where the (male) residual wage inequality increased. This aligns to evidence of a compressed wage structure disproportionately benefitting women relative to men. Furthermore, in countries where females moved up in the male residual wage distribution significantly ('mean female residual percentile') – namely in Austria, Ireland, Italy, the UK and the US – the 'gap effect' is negative. In other words, women's progression within education, experience and skill levels had a narrowing effect on the gender wage gap, while in Spain, the 'gap effect' widened the gender wage gap. Despite these differences, the 'gap effect' accounts for a substantial portion of the gender wage gap trends (more than one third) in most of the countries in our sample, except Portugal, where, despite the widening effect of the 'gap effect', the gender wage gap narrowed mainly due to improvements in women's education and experience levels as well as occupational skills.[20] It is also worth noting that 'gap effect' may capture the convergence in

[20] We also explored sensitivity of our results to the survey year. While the results are robust for all countries, findings for the UK are more sensitive. In particular, using 2009 data the change in returns to observed

the unobserved skills of males and females but also the changes in labour market institutions or discrimination. Indeed, Gayle and Golan (2012) develop a dynamic equilibrium model of labour supply, occupational sorting and human capital accumulation to quantify the driving forces behind the decline in the gender earnings gap in the US and find that the decline in labour market discrimination accounted for a large fraction of the decline in the gender wage gap between 1967 and 1997. Further investigation suggests that women in the US advanced in the male residual distribution (measured as the 'mean female residual percentile') much more between 1979 and 1988.[21] If a portion of the 'gap effect' is due to changes in discrimination, then such a sharp decline in discrimination in the 1980s would partially explain the larger contribution of the 'gap effect' to the change in the gender wage gap as compared to later decades. However, in the absence of direct measures, we are unable to explore the role of these factors further.

6. Conclusions

The recent literature focusing on the US has emphasised the role of various skills required by occupations and the changing prices of those skills with respect to narrowing the gender wage gap. In this paper, we explore gender wage gap trends in various European countries as well as in the US using direct measures of occupational skill requirements. We find that from 1994-1995 to 2008, brains became relatively more valuable than brawn in Austria, the UK and the US. As a result, part of the narrowing gender wage gap in these countries can be explained by the changes in (male) wage returns to brains and brawn. However, the increase in (male) wage

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characteristics has an important narrowing influence which acts to offset the influence of skill prices. Nevertheless, consistent with our main findings, using 2009 data we find that the 'gap effect' accounts for a substantial portion (88 per cent) of the narrowing gender wage gap in the UK (results available upon request).

[21] See Appendix Tables C3 and C4 for the wage regression estimates and decomposition results for the change in the US gender wage gap from 1979 to 1988.

returns to brains and the corresponding decrease to brawn were not a common phenomenon for Ireland, Italy, Portugal and Spain. In these countries, the changes in returns to brains and brawn had a widening effect on the gender wage gap. Nevertheless, with the exception of Spain, the gender wage gap declined in all countries between the two years. Consistent with previous evidence, we find that a compressed male residual wage distribution narrows the gender wage gap. We also find that, the change in unobserved factors, which may capture the convergence in the unobserved skills of males and females but also the changes in labour market institutions or discrimination, are an important determinant of the narrowing gender wage gap in several countries. In the absence of direct measures, however, we are unable to distinguish between the effects of unobserved productivity characteristics and labour market institutions or discrimination, which deserves future attention.

We conclude by commenting on the two important issues we have abstracted from, each of which might be important in future research. First, we abstracted from the heterogeneity of skills within occupations, which can be viewed as a shortcoming of our analysis. While this a major difficulty in all studies that combine occupational skill requirements with individual-level data, future efforts should be directed towards improving methods for combining this information with the self-reported data on workers' primary activities at their jobs. The second issue relates to the role of changes in the skill content of occupations over time on gender wage gap trends. Additional efforts should be made to conduct a more complete analysis of changes in the aggregate distribution of occupational skills.

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Tables

Table 1. Wage regression estimates

	Austria[a]		Ireland		Italy		Portugal		Spain		UK		US	
	1995	2008	1994	2008	1994	2008	1994	2008	1994	2008	1994	2008	1994	2008
Secondary education	0.120***	0.191**	0.256***	0.071	0.112***	0.127***	0.193***	0.267***	0.224***	0.138***	0.106***	0.174***	0.355***	0.325***
	(0.037)	(0.031)	(0.038)	(0.047)	(0.021)	(0.023)	(0.049)	(0.046)	(0.032)	(0.023)	(0.016)	(0.054)	(0.027)	(0.029)
High education	0.226***	0.370***	0.423***	0.358***	0.353***	0.287***	0.647***	0.617***	0.371***	0.280***	0.258***	0.345***	0.680***	0.691***
	(0.072)	(0.042)	(0.072)	(0.051)	(0.046)	(0.029)	(0.116)	(0.092)	(0.064)	(0.035)	(0.032)	(0.060)	(0.050)	(0.057)
Experience	0.002	0.027***	0.032***	0.039***	0.004	0.025***	0.014	0.047***	0.011**	0.032***	0.019***	0.012***	0.045***	0.042***
	(0.005)	(0.004)	(0.006)	(0.009)	(0.003)	(0.004)	(0.008)	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)	(0.006)	(0.004)
Experience^2	0.000	-0.000**	-0.000***	-0.001**	0.000	-0.000***	-0.000	-0.001***	-0.000	-0.001***	-0.000***	-0.000**	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Brains	0.581***	0.539***	0.675***	0.529***	0.384***	0.453***	0.766***	0.765***	0.689***	0.565***	0.690***	0.726***	0.603***	0.741***
	(0.132)	(0.072)	(0.169)	(0.128)	(0.105)	(0.089)	(0.241)	(0.113)	(0.186)	(0.112)	(0.133)	(0.068)	(0.145)	(0.144)
Brawn	-0.141***	-0.222***	-0.222**	-0.121	-0.283***	-0.152**	-0.550***	-0.332**	-0.334***	-0.248***	-0.161	-0.218***	-0.092	-0.122
	(0.041)	(0.042)	(0.103)	(0.082)	(0.069)	(0.057)	(0.121)	(0.095)	(0.083)	(0.081)	(0.119)	(0.064)	(0.100)	(0.087)
Constant	2.085***	1.752***	1.489***	1.703***	1.971***	1.678***	1.238***	0.979***	1.551***	1.648***	1.943***	2.166***	1.585***	1.646***
	(0.115)	(0.082)	(0.122)	(0.143)	(0.059)	(0.085)	(0.132)	(0.105)	(0.124)	(0.123)	(0.117)	(0.063)	(0.134)	(0.149)
VIF(Brains)	1.65	1.67	2.08	2.09	1.40	1.41	1.64	1.56	1.67	1.64	2.01	1.84	2.16	2.25
VIF(Brawn)	1.48	1.53	1.79	2.01	1.52	1.43	1.53	1.62	1.55	1.63	1.79	1.82	2.15	2.21
R-squared	0.14	0.29	0.34	0.36	0.32	0.28	0.43	0.40	0.35	0.34	0.27	0.25	0.25	0.27
Number of obs.	1,442	2,101	1,358	1,075	2,518	6,588	1,499	1,291	2,540	4,585	3,327	2,062	23,345	31,907

Data sources: European Community Household Panel (ECHP, 1994) ([a]For Austria, the 1995 wave of the ECHP is used, as it had joined the survey by then), European Union Statistics on Income and Living Conditions (EU-SILC, 2008) and Current Population Survey (CPS) March Supplements (1995 and 2009). Notes: (i) Reported are OLS hourly wage equation estimates for males. Occupational level clustered standard errors are in parentheses. (ii) *, ** and *** significant at 1, 5 and 10 % significance level, respectively. (iii) The omitted category is taken as primary education level for education dummies. (iv) Variance inflation factor: $VIF = 1/(1 - R_i^2)$ and R_i^2 is the coefficient of determination of the regression equation where each explanatory variable regressed on all the other explanatory variables.

Table 2. Decomposition of the change in the gender wage gap

Panel A. Descriptive statistics	Austria[a]	Ireland	Italy	Portugal	Spain	UK	US
Male residual SD							
1994-1995	0.405	0.422	0.301	0.433	0.415	0.418	0.546
2008	0.349	0.396	0.312	0.425	0.355	0.444	0.578
Mean female residual from male wage regression							
1994-1995	-0.270	-0.267	-0.124	-0.234	-0.164	-0.276	-0.316
2008	-0.225	-0.123	-0.091	-0.237	-0.185	-0.216	-0.289
Mean female residual percentile							
1994	30.92	32.85	38.53	33.20	38.52	30.49	33.11
2008	32.78	42.23	41.73	33.77	37.70	34.13	34.02
Panel B. Decomposition of the change in the gender wage gap							
Change in the gender wage gap	-0.069	-0.133	-0.029	-0.010	0.053	-0.073	-0.060
Gender wage gap, 1994-1995	0.275	0.233	0.075	0.174	0.082	0.300	0.270
Gender wage gap, 2008	0.207	0.100	0.046	0.164	0.135	0.227	0.210
(1) Observed characteristics	0.005	-0.005	-0.040	-0.062	0.023	-0.014	-0.032
Observed *X*'s effect	0.011	-0.004	-0.028	-0.042	0.006	-0.005	-0.019
Observed *S*'s effect	-0.006	0.001	-0.012	-0.020	0.017	-0.009	-0.013
(2) Observed prices	-0.004	0.028	0.044	0.051	0.038	-0.010	-0.014
Observed *X* prices effect	0.010	0.012	0.020	0.016	0.025	-0.005	-0.002
Observed *S* prices effect	-0.014	0.016	0.024	0.035	0.013	-0.005	-0.012
(3) Unobserved prices effect	-0.026	-0.015	0.001	-0.005	-0.029	0.010	0.012
(4) Gap effect	-0.044	-0.141	-0.033	0.006	0.022	-0.059	-0.026

Data sources: European Community Household Panel (ECHP, 1994) ([a]For Austria, the 1995 wave of the ECHP is used, as it had joined the survey by then), European Union Statistics on Income and Living Conditions (EU-SILC, 2008) and Current Population Survey (CPS) March Supplements (1995 and 2009). Notes: (i) Mean female residual from male wage regression is estimated using male wage regression. (ii) Mean female residual percentile is computed by assigning each women a percentile ranking in the indicated year's residual male wage distribution and calculating the female mean of these percentiles. (iii) Juhn-Murphy-Pierce (1991) method is used to decompose the change in the gender wage gap using the male coefficients as reference and 1994 (for Austria, 1995) as benchmark.

Appendices (for online-only publication)

Appendix A. Data appendix

Data sources

European Community Household Panel (ECHP): The ECHP is a standardised annual longitudinal survey which run from 1994 to 2001 (8 waves) at the level of the European Union. The then Member States included in the ECHP are Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, the Netherlands, Austria, Portugal, Sweden and the UK. ECHP is designed and coordinated by the Statistical Office of the European Communities (Eurostat), covering a wide range of topics like income, health, education, housing, demographics and employment characteristics for a sample of households and persons who has been interviewed year after year. From 2001, the ECHP was succeeded by the EU-SILC which covers most of the above-mentioned topics as from 2003/2004.

European Union Statistics on Income and Living Conditions (EU-SILC): The successor of the ECHP, the EU-SILC, launched in 2003 providing annual cross-sectional data on income, poverty, social exclusion, and other living conditions as well as longitudinal data pertaining to individual-level changes observed over a four-year period. Different than its predecessor ECHP, the EU-SILC is not based on harmonised questionnaires with Member States being allowed to use different survey instruments to collect a set of social and economic indicators which should be provided by the data set i.e. output-harmonised. Hence the number of annual EU-SILC target primary variables is lower than those in ECHP, but the majority of variables are defined in the same way as the corresponding ECHP variables.[22]

[22] See https://ec.europa.eu/eurostat/ramon/statmanuals/files/transition_echp_eu-silc.pdf for a comparison between the ECHP and EU-SILC.

Current Population Survey (CPS): For the US, data come from Integrated Public Use Microdata Series (IPUMS) CPS March Supplements. The CPS is a nationally representative monthly labour survey of approximately 60,000 households who are interviewed for four consecutive months, drop out of the sample for eight consecutive months, and then are interviewed again for another four consecutive months before leaving the survey permanently. The CPS records the basic demographic and work-related characteristics for each individual in the household and every March it includes a supplementary set of questions that contain questions on income received by the respondents in the previous calendar year which have been used in the literature to construct data on wages (see, for example, Katz and Murphy, 1992; Acemoglu and Autor, 2011).

Occupational Information Network (O*Net): Our occupational skill data come from the O*NET 15.0 (released in June 2010) database, which was developed by the US Department of Labour. O*Net provides detailed information about worker and job characteristics for more than a thousand occupations and is the most well-known source for information on occupations in the US labour market. It is a replacement for the Dictionary of Occupational Titles (DOT), which has been extensively used in earlier research (see, for example, Autor, Levy and Murnane 2003; Bacolod and Blum 2010; Goos and Manning 2007).

Variable definitions

Gross hourly wage: Gross hourly wages from the ECHP and EU-SILC are constructed by dividing the *current* gross monthly earnings from main job including overtime (times 12/52) by usual hours in the main job including overtime.[23] Both datasets include supplementary information on PPP exchange rates. Wages are converted in 2005 PPP units using the purchasing power parity exchange rates and deflated with the harmonised consumer price index (HCPI, base 2005). Gross

[23] No information on overtime hours or pay was provided.

hourly wages from the CPS are constructed using the total pre-tax wage and salary income, that is, money received as an employee, for the *previous calendar year*, which are top coded. Following the common practice, the top-coded values of the annual gross wages are multiplied by the value 1.45. Wages are deflated by the consumer price index (CPI, base 2005). For generating an hourly amount, we divide annual gross wage by the number of weeks worked during the preceding calendar year times the total number of hours usually worked per week over all jobs the year prior to the survey (last year).

Occupation: The ECHP and EU-SILC occupations are classified according to the International Standard Classification of Occupations (ISCO-88) and coded at the two-digit level. The CPS occupations, however, are classified according to the Standard Occupational Classification (SOC) 2000.[24] To map occupations across datasets, we use the ISCO-SOC 2000 mapping made publicly available by the Centre for Longitudinal Studies in the UK. In all the three datasets, we categorise occupations into 18 categories using the cluster of variable PE006B (occupation in current job) in the ECHP.

Education: The education variable from the ECHP and EU-SILC is harmonised by using the International Standard Classification of Education (ISCED) categories. Low education is defined as having no qualifications or only qualifications below the secondary education level and corresponds to the ISCED categories 0-2. Secondary education is defined by the ISCED categories 3-4 and includes all second stage of secondary level education. High educational qualification is defined by the ISCED categories 5-7 and includes recognised third level education. Educational attainment variable from the CPS is reclassified based on the ISCED categories using the mapping provided publicly by UNESCO Institute for Statistics.

Work experience: The EU-SILC cross-sectional component provides exact number of years spent in paid work for all countries in our sample. However, for

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[24] To match the income reference period of wages in CPS, we use information on occupation for the previous year.

the UK, more than 90 per cent of the original is missing this information.[25] Therefore, for the UK, we use a proxy for work experience that is years passed after the highest level of education was attained. The ECHP lacks information on actual labour market experience. However, it provides information about 1) age when highest level of education was completed, 2) age at the beginning of the working life, and 3) the number of continuous months of unemployment before current job.[26] Using these three variables, we generate a proxy for work experience. Formally, let y_t denote the year of the survey, y_s the year when the individual attained the highest education level, y_w the year when the individual began working life and m_u the number of continuous months of unemployment before current job ($y_u = m_u/12$ in years). The proxy measure for work experience for individuals who completed their education earlier than starting to the working life (if $y_s \geq y_w$) is computed as $exp\ = y_t - y_w$ and for individuals who started their working life before completing their highest education degree (if $y_s > y_w$) as $exp\ = y_t - y_s$. Then, we correct our proxy measure by subtracting the continuous months of unemployment before current job ($exp^* \ = \ exp - y_u$). Since the CPS does not provide information on actual work experience, we use potential labour market experience, that is age minus years of schooling minus six, where years of schooling is imputed based on the educational attainment levels as suggested by Jaeger (1997).

*Mapping of the O*NET data, with an extended version of SOC-10 to ISCO-88*

The O*NET data (v15.0) use an extended version of the Standard Occupational Classification 2010 (SOC-10). We use two crosswalks (ISCO-SOC 2000 crosswalk by the Centre for Longitudinal Studies in the UK and the SOC 2000-SOC 2010 crosswalk by the Integrated Public Use Microdata Series (IPUMS-USA)) for mapping SOC-10 and ISCO-88 occupations. As the variable PE006B (occupation in current job) in the ECHP has 18 occupation categories, this requires mapping

[25] This is due to an error on the UK questionnaire through 2008 and January-September 2009. See, for further details, https://circabc.europa.eu/sd/a/01eaed18-f838-49d5-8b9c-36ddc934eb4e/SILC%20ESQRS%20UK%202011.htm.

[26] We complete missing information on age when highest level of education using the latter waves as the ECHP has the longitudinal structure.

several O*NET occupations into one broad occupation category.[27] Therefore, we map several O*NET occupations into a small number of occupation categories by calculating a weighted average across the component O*NET occupations, where the weights correspond to 2001 US employment data reported by the Bureau of Labor Statistics (2010).

*Mapping of the O*NET data, with an extended version of SOC-10 to SOC-10*

Both O*NET and CPS use SOC-10 occupational classification, however, there exist some differences between the two datasets. O*NET includes 1,110 occupations and for 974 of them provides detailed information on worker abilities, while SOC-10 includes 840 detailed occupations. There is a one-to-one correspondence of the O*NET occupations to SOC-10. However, 37 SOC-10 occupations are divided into multiple categories in the O*NET data. For instance, SOC-10 code 11-3031 is Financial Managers, which is further disaggregated by the O*Net into two categories: 11-3031.01, Treasurers and Controllers, and 11-3031.02 Financial Managers, Branch or Department. For these two categories, O*Net includes occupational skill requirements separately (both for 11-3031.01 and 11-3031.02) but also at the aggregate level (for 11-3031). In these cases, we simply consider the occupational skill descriptive values for the main title (for 11-3031). However, 269 O*Net occupations do not exist in SOC-10 as separate categories. For instance, SOC-10 occupation 13-2011 Accountants and Auditors is disaggregated into 13-2011.01 Accountants and 13-2011.02 Auditors. For these cases, we take a simple mean of the O*Net descriptor values to determine the skill requirement of the main title (13-2011).[28]

[27] For Portugal, we regroup two occupations: 1112-Legislators, senior officials and corporate managers and 1300-Managers of small enterprises, as the EU-SILC does not differentiate between these two.

[28] The only exception, 19-1020.01 Biologists does not exist in the SOC-10 classification and hence, we excluded it from the analysis.

Table A1. List of O*NET variables comprising brains and brawn

Variables comprising BRAINS

O*Net Variable	Description
oral comprehension	listening and understanding information and ideas presented through spoken words and sentences
written comprehension	reading and understanding information and ideas presented in writing
oral expression	communicating information and ideas in speaking so others will understand
written expression	communicating information and ideas in writing so others will understand
fluency of ideas	coming up with a number of ideas about a topic
originality	coming up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem
problem sensitivity	telling when something is wrong or is likely to go wrong
deductive reasoning	applying general rules to specific problems to produce answers that make sense
inductive reasoning	combining pieces of information to form general rules or conclusions
information ordering	arranging things or actions in a certain order or pattern according to a specific rule or set of rules
category flexibility	generating or using different sets of rules for combining or grouping things in different ways
mathematical reasoning	choosing the right mathematical methods or formulas to solve a problem
number facility	adding, subtracting, multiplying, or dividing quickly and correctly
memorization	remembering information such as words, numbers, pictures, and procedures
speed of closure	quickly making sense of, combining, and organizing information into meaningful patterns
flexibility of closure	identifying or detecting a known pattern that is hidden in other distracting material
perceptual speed	quickly and accurately comparing similarities and differences among sets of letters, numbers, objects, pictures, or patterns
spatial orientation	knowing the location in relation to the environment
visualization	imagining how something will look after it is moved around or when its parts are moved or rearranged
selective attention	concentrating on a task over a period of time without being distracted
time sharing	shifting back and forth between two or more activities or sources of information
social perceptiveness	being aware of others' reactions and understanding why they react as they do
coordination	adjusting actions in relation to others' actions
persuasion	persuading others to change their minds or behaviour
negotiation	bringing others together and trying to reconcile differences
instructing	teaching others how to do something
service orientation	actively looking for ways to help people

Variables comprising BRAWN

O*Net Variable	Description
arm-hand steadiness	keeping hand and arm steady while moving arm or while holding arm and hand in one position
manual dexterity	quickly moving hand, hand together with arm, or two hands to grasp, manipulate, or assemble objects
finger dexterity	making precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects
control precision	quickly and repeatedly adjusting the controls of a machine or a vehicle to exact positions
multi-limb coordination	coordinating two or more limbs while sitting, standing, or lying down
response orientation	choosing quickly between two or more movements in response to two or more different signals
rate control	timing movements or the movement of a piece of equipment in anticipation of changes in the speed and/or direction of a moving object or scene
reaction time	quickly responding to a signal when it appears
wrist-finger speed	making fast, simple, repeated movements of the fingers, hands, and wrists
speed of limb movement	quickly moving the arms and legs
static strength	exerting maximum muscle force to lift, push, pull, or carry objects
explosive strength	using short bursts of muscle force to propel oneself, or to throw an object
dynamic strength	exerting muscle force repeatedly or continuously over time
trunk strength	using abdominal and lower back muscles to support part of the body repeatedly or continuously over time without giving out or fatiguing
stamina	exerting physically over long periods of time without getting winded or out of breath
extent flexibility	bending, stretching, twisting, or reaching with body, arms, and/or legs
dynamic flexibility	quickly and repeatedly bending, stretching, twisting, or reaching out with body, arms, and/or legs
gross body coordination	coordinating the movement of arms, legs, and torso together when the whole body is in motion
gross body equilibrium	keeping or regaining body balance or stay upright when in an unstable position

Table A2. Occupational skill requirements

Brains	Brawn	Occupation title
0.77	0.16	Legislators, senior officials, corporate managers
0.79	0.09	Managers of small enterprises
0.81	0.33	Physical, mathematical, engineering, life science, health professionals
0.77	0.09	Teaching professionals
0.69	0.12	Other professionals
0.62	0.51	Physical, engineering, life science, health associate professionals
0.56	0.07	Teaching and other associate professionals
0.42	0.22	Office and customer services clerks
0.40	0.64	Personal and protective services workers
0.52	0.35	Models, salespersons and demonstrators
0.25	0.81	Skilled agricultural and fishery workers
0.42	0.87	Extraction, building, other craft and related trades workers
0.41	0.78	Metal, machinery, precision, handicraft, printing and related trades workers
0.41	0.83	Stationary-plant and related operators, drivers and mobile-plant operators
0.27	0.64	Machine operators and assemblers
0.04	0.55	Sales and services elementary occupations
0.49	0.79	Agricultural, fishery and related labourers
0.13	0.76	Labourers in mining, construction, manufacturing and transport
0.46	0.44	Mean
0.22	0.28	Std. dev.
-0.67		Pearson correlation coefficient

Note: Occupation codes are based on the regrouped classification of the ECHP (variable PE006B). Occupational skill requirements are constructed using data from the O*NET (v.15.0) database.

Table A3. Sample statistics

Panel A. 1994-1995

	Austria[a]		Ireland		Italy		Portugal		Spain		UK		US	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
log(hourly wage)	2.177	2.452	2.083	2.316	2.076	2.151	1.324	1.498	1.909	1.991	2.264	2.564	2.561	2.831
	(0.546)	(0.436)	(0.558)	(0.521)	(0.396)	(0.364)	(0.632)	(0.575)	(0.544)	(0.513)	(0.464)	(0.488)	(0.611)	(0.630)
Primary edu (%)	23.53	14.78	22.22	34.89	38.69	50.17	70.72	78.37	39.45	52.79	43.77	35.60	3.44	6.09
Secondary edu (%)	66.67	76.65	51.31	39.74	48.31	38.44	14.91	12.20	20.74	19.48	25.70	26.04	58.57	56.53
High edu (%)	9.79	8.57	26.47	25.37	13.00	11.39	14.37	9.42	39.81	27.73	30.52	38.36	37.99	37.38
Experience (year)	17.039	16.464	15.564	18.172	14.100	16.345	15.505	19.043	13.772	17.421	18.634	17.660	18.864	18.634
	(9.741)	(9.677)	(9.045)	(9.448)	(9.471)	(9.886)	(9.655)	(9.906)	(9.725)	(10.568)	(10.469)	(9.902)	(8.523)	(8.433)
Brains	0.420	0.461	0.500	0.491	0.447	0.429	0.424	0.449	0.461	0.456	0.502	0.534	0.512	0.482
	(0.192)	(0.177)	(0.207)	(0.201)	(0.190)	(0.175)	(0.190)	(0.161)	(0.238)	(0.181)	(0.203)	(0.206)	(0.208)	(0.225)
Brawn	0.382	0.555	0.336	0.494	0.379	0.512	0.474	0.584	0.363	0.552	0.336	0.440	0.323	0.466
	(0.235)	(0.294)	(0.215)	(0.300)	(0.266)	(0.293)	(0.278)	(0.285)	(0.245)	(0.291)	(0.219)	(0.291)	(0.235)	(0.303)
Number of obs.	952	1,442	944	1,358	1,568	2,518	1,125	1,499	1,274	2,540	3,114	3,327	22,248	23,345

Panel B. 2008

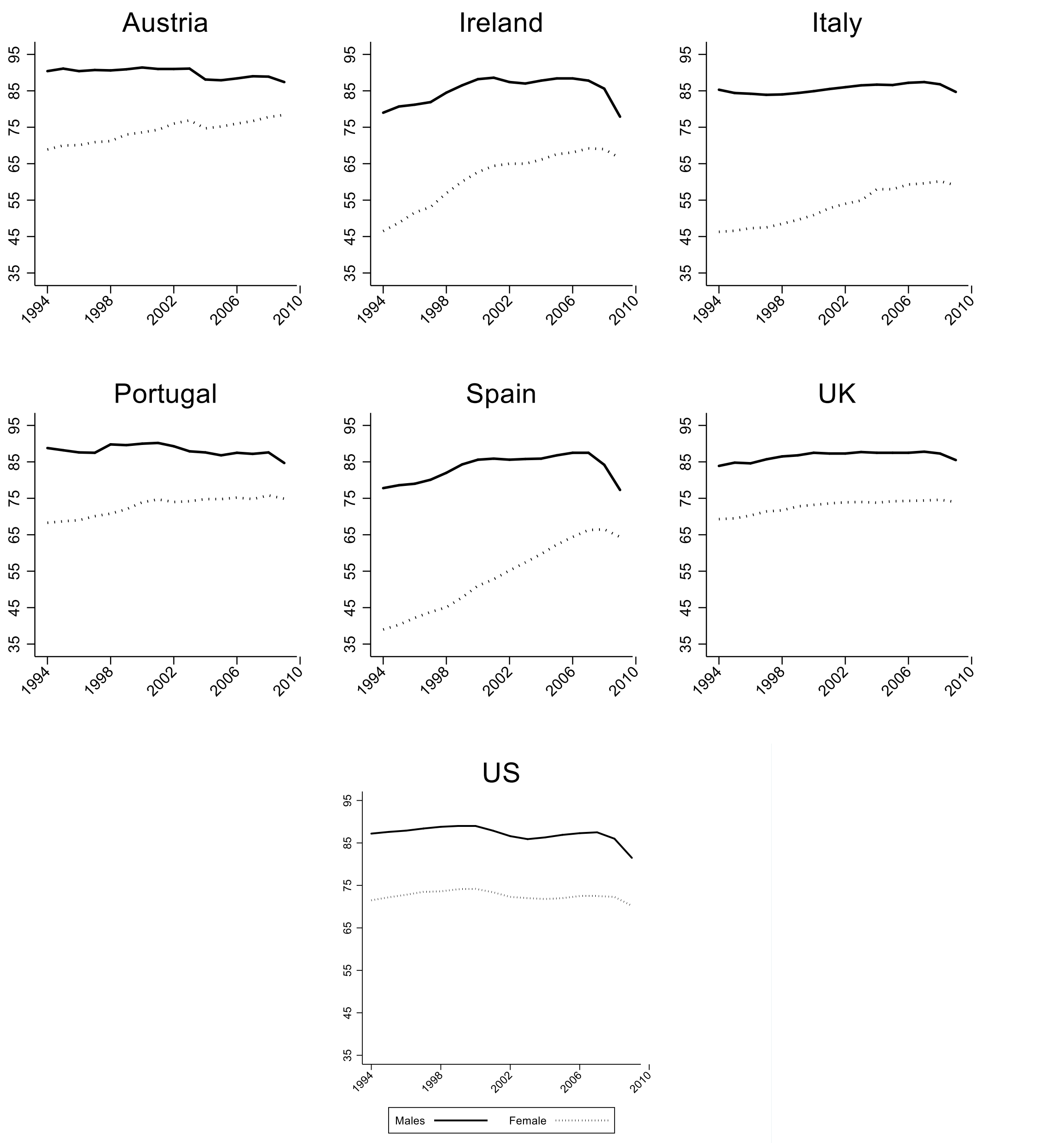
	Austria		Ireland		Italy		Portugal		Spain		UK		US	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
log(hourly wage)	2.274	2.481	2.525	2.625	2.147	2.194	1.569	1.732	2,152	2.288	2.624	2.851	2.664	2.874
	(0.429)	(0.415)	(0.494)	(0.494)	(0.403)	(0.366)	(0.554)	(0.549)	(0.470)	(0.437)	(0.483)	(0.511)	(0.630)	(0.677)
Primary edu (%)	13.42	8.11	16.39	24.71	28.10	43.29	59.01	71.09	27.11	37.97	0.77	0.73	3.37	5.94
Secondary edu (%)	50.73	58.22	22.90	26.82	42.42	39.19	18.64	16.89	25.04	23.74	52.42	52.22	47.99	53.55
High edu (%)	35.85	32.97	60.71	48.47	29.48	17.52	22.34	12.02	47.85	38.29	46.81	47.05	48.64	40.51
Experience (year)	18.855	21.208	16.055	19.178	15.019	17.388	18.399	20.878	15.018	18.332	14.819	15.650	19.788	19.736
	(8.862)	(9.152)	(9.127)	(9.841)	(8.663)	(9.349)	(9.822)	(10.081)	(8.786)	(9.594)	(10.391)	(9.522)	(9.263)	(9.061)
Brains	0.449	0.475	0.549	0.529	0.467	0.457	0.409	0.445	0.450	0.461	0.533	0.550	0.535	0.485
	(0.209)	(0.190)	(0.206)	(0.219)	(0.189)	(0.167)	(0.221)	(0.166)	(0.224)	(0.191)	(0.184)	(0.224)	(0.205)	(0.222)
Brawn	0.361	0.517	0.321	0.450	0.357	0.544	0.443	0.604	0.368	0.537	0.307	0.407	0.312	0.463
	(0.237)	(0.295)	(0.215)	(0.298)	(0.254)	(0.286)	(0.256)	(0.281)	(0.228)	(0.291)	(0.210)	(0.280)	(0.228)	(0.304)
Number of obs.	1,760	2,101	1,148	1,075	5,435	6,588	1,217	1,291	4,055	4,585	2,222	2,062	31,018	31,907

Data sources: For the year 1994, the European Community Household Panel (ECHP) in 1994 and Current Population Survey (CPS) March Supplements in 1995. [a]For Austria, the 1995 wave of the ECHP is used, as it had joined the survey by then. For the year 2008, the European Union Statistics on Income and Living Conditions (EU-SILC) in 2008 and CPS March Supplements in 2009. Notes: See Data Appendix for variable definitions.

Table A4. Sample statistics for brains and brawn

	Austria[a]		Ireland		Italy		Portugal		Spain		UK		US	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Brains														
t	0.420	0.461	0.500	0.491	0.447	0.429	0.424	0.449	0.461	0.456	0.502	0.534	0.512	0.482
t′	0.449	0.475	0.549	0.529	0.467	0.457	0.409	0.445	0.450	0.461	0.533	0.550	0.535	0.485
Δ *t′-t*	0.029	0.014	0.049	0.038	0.02	0.028	-0.015	-0.004	-0.011	0.005	0.031	0.016	0.023	0.003
Gender gap in *t*	0.041		-0.009		-0.018		0.025		-0.005		0.032		-0.030	
Gender gap in *t′*	0.026		-0.020		-0.010		0.036		0.011		0.017		-0.050	
ΔGap *t′-t*	-0.015		-0.011		0.008		0.011		0.016		-0.015		-0.020	
Brawn	-0.021	-0.038	-0.015	-0.044	-0.022	0.032	-0.031	0.02	0.005	-0.015	-0.029	-0.033	-0.011	-0.003
t	0.382	0.555	0.336	0.494	0.379	0.512	0.474	0.584	0.363	0.552	0.336	0.440	0.323	0.466
t′	0.361	0.517	0.321	0.450	0.357	0.544	0.443	0.604	0.368	0.537	0.307	0.407	0.312	0.463
Δ *t′-t*	-0.021	-0.038	-0.015	-0.044	-0.022	0.032	-0.031	0.020	0.005	-0.015	-0.029	-0.033	-0.011	-0.003
Gender gap in *t*	0.173		0.158		0.133		0.110		0.189		0.104		0.143	
Gender gap in *t′*	0.156		0.129		0.187		0.161		0.169		0.100		0.151	
ΔGap *t′-t*	-0.017		-0.029		0.054		0.051		-0.020		-0.004		0.008	

Data sources: For the year 1994, the European Community Household Panel (ECHP) in 1994 and Current Population Survey (CPS) March Supplements in 1995. [a]For Austria, the 1995 wave of the ECHP is used, as it had joined the survey by then. For the year 2008, the European Union Statistics on Income and Living Conditions (EU-SILC) in 2008 and CPS March Supplements in 2009. Notes: See Data Appendix for variable definitions. **Δ** represents the difference in mean values between the year *t'*=2008 and *t*=1994 (1995 for Austria).



Data source: OECD.Stat, Employment population ratio of men and women in the prime ages of 25-54 years (data extracted on 5 April 2021).

Figure A1. Employment rates over time, by country and gender

Appendix B. Constructing brains and brawn through Principal Component Analysis (PCA)

PCA is a variable reduction technique which maximises the amount of variance accounted for in the observed variables by a smaller group of variables called principal components. PCA has been widely used in the literature to construct task or skill measures from the various descriptors of the DOT and the O*NET databases by performing separate PCA for different sets of selected standardised descriptors (mean zero and variance one) and using the first principal component of each analysis as the summary measure for that set of variables.[29]

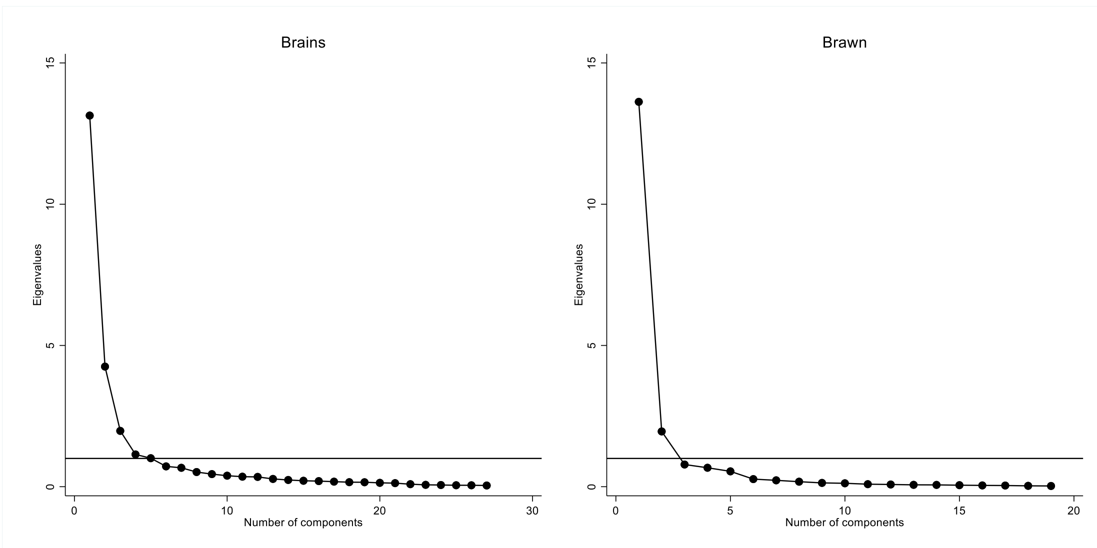


Figure B1. Scree plot of eigenvalues

As a sensitivity analysis, we construct alternative skill measures through performing separate PCA for 1) cognitive ability and social skill descriptors 2) psycho-motor abilities and physical ability descriptors using the 849 O*NET occupations matched with ISCO level occupations. The first principal component performed using the O*NET descriptors that measure cognitive abilities and social skills explains around 50 per cent of the variation among these descriptors, while

[29] It is worth noting that the components are not latent factors. As such PCA is not a model-based technique and involves no hypothesis about the substantive meaning of or relationships between latent factors.

most of the variation among the psycho-motor and physical ability descriptors are explained by the first principal component (around 72 per cent of the variation). Figure B.1 visually presents the ability of first principal components of each analysis to explain the variation in corresponding O*NET variables values.

Table B1. Principal component loadings

Brains		Brawn	
Descriptor	Component Loading	Descriptor	Component Loading
Oral comprehension	0.217	Arm-hand steadiness	0.241
Written comprehension	0.222	Manual dexterity	0.241
Oral expression	0.206	Finger dexterity	0.177
Written expression	0.223	Control precision	0.233
Fluency of ideas	0.232	Multi-limb coordination	0.258
Originality	0.222	Response orientation	0.238
Problem sensitivity	0.211	Rate control	0.235
Deductive reasoning	0.243	Reaction time	0.241
Inductive reasoning	0.238	Wrist-finger speed	0.214
Information ordering	0.203	Speed of limb movement	0.241
Category flexibility	0.208	Static strength	0.257
Mathematical reasoning	0.169	Explosive strength	0.123
Number facility	0.155	Dynamic strength	0.250
Memorization	0.205	Trunk strength	0.240
Speed of closure	0.188	Stamina	0.246
Flexibility of closure	0.163	Extent flexibility	0.252
Perceptual speed	0.093	Dynamic flexibility	0.140
Spatial orientation	-0.055	Gross body coordination	0.244
Visualization	0.052	Gross body equilibrium	0.234
Selective attention	0.143		
Time sharing	0.156		
Social perceptiveness	0.198		
Coordination	0.214		
Persuasion	0.218		
Negotiation	0.212		
Instructing	0.202		
Service orientation	0.173		

Principal components based on transformation of correlation matrix to eigen-basis coordinates are unit free. If all the O*NET variables related to the same skill in the corresponding component has a positive loading, then a higher component score implies a higher intensity in that skill. Table B1 presents each descriptor's component loading from the PCA for brains and brawn. With the exception of 'spatial orientation', all cognitive ability and social skill descriptors have a positive weight on the first principal component of the former PCA, while all psycho-motor and physical ability descriptors have a positive loading on the first component of the latter. Therefore, these two components constitute our alternative measures of brains and brawn in the sensitivity analysis. As in the benchmark analysis, we map several O*NET occupations to a small number of occupation categories by calculating a weighted average across the component O*NET occupations, where the weights correspond to 2001 US employment data reported by the Bureau of Labor Statistics (2010). Table B2 presents the summary statistics of standardised occupational skill measures (with a zero mean, a unit variance) constructed through this procedure.

Table B2. Occupational skill requirements constructed through PCA

Principal Component Values		Occupation
Brains	Brawn	
1.291	-1.046	Legislators, senior officials and corporate managers
1.206	-1.272	Managers of small enterprises
1.374	-0.566	Physical, mathematical, engineering, life science and health professionals
1.348	-1.284	Teaching professionals
0.988	-1.220	Other professionals
0.540	0.075	Physical, engineering, life science and health associate professionals
0.472	-1.347	Teaching and other associate professionals
-0.203	-0.856	Office and customer services clerks
-0.345	0.461	Personal and protective services workers
0.250	-0.440	Models, salespersons and demonstrators
-1.090	1.101	Skilled agricultural and fishery workers
-0.312	1.223	Extraction, building, other craft and related trades workers
-0.441	0.993	Metal, machinery, precision, handicraft, printing and related trades workers
-0.602	1.286	Stationary-plant and related operators, drivers and mobile-plant operators
-0.985	0.610	Machine operators and assemblers
-1.811	0.243	Sales and services elementary occupations
-0.147	1.113	Agricultural, fishery and related labourers
-1.532	0.926	Labourers in mining, construction, manufacturing and transport
0	0	Mean
1	1	Std. dev.
0.747		Pearson correlation coefficient

Note: Occupation codes are based on the regrouped classification of the ECHP (variable PE006B). Occupational skill requirements are constructed using data from the O*NET (v.15.0) database.

Appendix C. Sensitivity analysis

Table C1. Wage regression estimates using occupational skill measures constructed through PCA

	Austria[a]		Ireland		Italy		Portugal		Spain		UK		US	
	1995	2008	1994	2008	1994	2008	1994	2008	1994	2008	1994	2008	1994	2008
Secondary education	0.119***	0.192***	0.247***	0.069	0.117***	0.128***	0.196***	0.273***	0.227***	0.141***	0.101***	0.167***	0.355***	0.327***
	(0.037)	(0.031)	(0.037)	(0.047)	(0.023)	(0.022)	(0.048)	(0.045)	(0.032)	(0.022)	(0.016)	(0.052)	(0.027)	(0.029)
High education	0.225***	0.369***	0.407***	0.355***	0.361***	0.288***	0.653***	0.630***	0.374***	0.284***	0.248***	0.337***	0.675***	0.689***
	(0.071)	(0.043)	(0.067)	(0.052)	(0.049)	(0.028)	(0.116)	(0.093)	(0.065)	(0.035)	(0.031)	(0.059)	(0.049)	(0.056)
Experience	0.002	0.027***	0.032***	0.039***	0.004	0.025***	0.014	0.047***	0.011**	0.032***	0.019***	0.012***	0.045***	0.042***
	(0.005)	(0.004)	(0.006)	(0.009)	(0.003)	(0.004)	(0.008)	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)	(0.006)	(0.004)
Experience^2	0.000	-0.000***	-0.000***	-0.001*	0.000	-0.000***	-0.000	-0.001***	-0.000	-0.001***	-0.000***	-0.000**	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Brains	0.144***	0.133***	0.178***	0.137***	0.089***	0.110***	0.182***	0.179***	0.165***	0.137***	0.180***	0.181***	0.157***	0.190***
	(0.032)	(0.018)	(0.040)	(0.031)	(0.026)	(0.022)	(0.061)	(0.028)	(0.045)	(0.028)	(0.030)	(0.018)	(0.037)	(0.037)
Brawn	-0.023	-0.050***	-0.041	-0.016	-0.072***	-0.030	-0.140***	-0.075**	-0.078**	-0.056*	-0.021	-0.041**	-0.007	-0.013
	(0.016)	(0.015)	(0.035)	(0.024)	(0.025)	(0.020)	(0.041)	(0.033)	(0.029)	(0.028)	(0.036)	(0.019)	(0.032)	(0.028)
Constant	2.301***	1.906***	1.722***	1.904***	2.017***	1.825***	1.345***	1.184***	1.721***	1.799***	2.208***	2.422***	1.838***	1.946***
	(0.060)	(0.054)	(0.084)	(0.088)	(0.032)	(0.044)	(0.090)	(0.073)	(0.062)	(0.060)	(0.043)	(0.058)	(0.085)	(0.084)
R-squared	0.137	0.292	0.346	0.359	0.314	0.274	0.432	0.398	0.343	0.335	0.272	0.248	0.249	0.271
Number of obs.	1,442	2,101	1,358	1,075	2,518	6,588	1,499	1,291	2,540	4,585	3,327	2,062	23,345	31,907

Data source: For the year 1994, the European Community Household Panel (ECHP) in 1994 and Current Population Survey (CPS) March Supplements in 1995. [a]For Austria, the 1995 wave of the ECHP is used, as it had joined the survey by then. For the year 2008, the European Union Statistics on Income and Living Conditions (EU-SILC) in 2008 and CPS March Supplements in 2009. Notes: (i) Reported are OLS hourly wage equation estimates for males. Occupational level clustered standard errors are in parentheses. (ii) *, ** and *** significant at 1, 5 and 10 % significance level, respectively. (iii) The omitted category is taken as primary education level for education dummies. (iv) Variance inflation factor: $VIF = 1/(1-R_i^2)$ and R_i^2 is the coefficient of determination of the regression equation where each explanatory variable regressed on all the other explanatory variables.

Table C2. Wage regression estimates, returns to Brains/Brawn

	Austria[a]		Ireland		Italy		Portugal		Spain		UK		US	
	1995	2008	1994	2008	1994	2008	1994	2008	1994	2008	1994	2008	1994	2008
Secondary education	0.175***	0.242***	0.314***	0.097**	0.154***	0.161***	0.316***	0.328***	0.268***	0.173***	0.144***	0.237***	0.399***	0.371***
	(0.048)	(0.028)	(0.049)	(0.039)	(0.018)	(0.035)	(0.057)	(0.049)	(0.046)	(0.027)	(0.022)	(0.059)	(0.030)	(0.037)
High education	0.356***	0.490***	0.587***	0.406***	0.425***	0.379***	0.888***	0.794***	0.503***	0.389***	0.365***	0.476***	0.781***	0.796***
	(0.094)	(0.054)	(0.099)	(0.062)	(0.055)	(0.054)	(0.085)	(0.161)	(0.100)	(0.071)	(0.047)	(0.085)	(0.075)	(0.083)
Experience	0.000	0.025***	0.034***	0.039***	0.003	0.025***	0.012	0.046***	0.011**	0.030***	0.019***	0.014***	0.045***	0.042***
	(0.005)	(0.004)	(0.005)	(0.009)	(0.000)	(0.003)	(0.009)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.006)	(0.004)
Experience^2	0.000	-0.000**	-0.000***	-0.001**	0.000	-0.000***	-0.000	-0.001***	-0.000	-0.000***	-0.000***	-0.000**	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Brains/Brawn	0.034***	0.036***	0.038**	0.047***	0.046***	0.025***	0.064***	0.058***	0.053***	0.042***	0.041**	0.052***	0.035***	0.047***
	(0.011)	(0.008)	(0.015)	(0.012)	(0.012)	(0.009)	(0.017)	(0.011)	(0.014)	(0.013)	(0.015)	(0.017)	(0.008)	(0.009)
Constant	2.167***	1.765***	1.533***	1.766***	1.888***	1.728***	1.136***	1.004***	1.534***	1.654***	2.081***	2.216***	1.672***	1.750***
	(0.063)	(0.051)	(0.072)	(0.093)	(0.028)	(0.040)	(0.093)	(0.058)	(0.061)	(0.047)	(0.054)	(0.054)	(0.070)	(0.069)
R-squared	0.104	0.242	0.300	0.343	0.309	0.243	0.375	0.376	0.305	0.303	0.213	0.174	0.228	0.250
Number of obs.	1,442	2,101	1,358	1,075	2,518	6,588	1,499	1,291	2,540	4,585	3,327	2,062	23,345	31,907

Data source: For the year 1994, the European Community Household Panel (ECHP) in 1994 and Current Population Survey (CPS) March Supplements in 1995. [a]For Austria, the 1995 wave of the ECHP is used, as it had joined the survey by then. For the year 2008, the European Union Statistics on Income and Living Conditions (EU-SILC) in 2008 and CPS March Supplements in 2009. Notes: (i) Reported are OLS hourly wage equation estimates for males. Occupational level clustered standard errors are in parentheses. (ii) *, ** and *** significant at 1, 5 and 10 % significance level, respectively. (iii) The omitted category is taken as primary education level for education dummies. (iv) Variance inflation factor: $VIF = 1/(1-R_i^2)$ and R_i^2 is the coefficient of determination of the regression equation where each explanatory variable regressed on all the other explanatory variables.

Table C3. Wage regression estimates for the US, 1979-1988 vs. 1994-2008

	1979	1988	1994	2008
Secondary Education	0.320***	0.352***	0.355***	0.325***
	(0.034)	(0.045)	(0.027)	(0.029)
Higher Education	0.481***	0.589***	0.680***	0.691***
	(0.061)	(0.061)	(0.050)	(0.057)
Experience	0.043***	0.049***	0.045***	0.042***
	(0.006)	(0.003)	(0.006)	(0.004)
Experience sq.	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Brains	0.470***	0.613***	0.603***	0.741***
	(0.140)	(0.146)	(0.145)	(0.144)
Brawn	0.016	-0.066	-0.092	-0.122
	(0.096)	(0.110)	(0.100)	(0.087)
Constant	1.934***	1.664***	1.585***	1.646***
	(0.151)	(0.151)	(0.134)	(0.149)
VIF(Brains)	2.12	2.19	2.16	2.25
VIF(Brawn)	2.13	2.21	2.15	2.21
R-squared	0.164	0.230	0.249	0.271
Number of obs.	22,691	20,446	23,345	31,907

Data source: CPS March Supplements (for years 1980, 1989, 1995 and 2009). Notes: i) Reported are OLS hourly wage equation estimates for males. Occupational level clustered standard errors are in parentheses. (ii)*, ** and *** significant at 1, 5 and 10 % significance level respectively. (iii) The omitted category is taken as low level for education dummies. (iv) Variance inflation factor: $VIF = 1/(1-R^2)$ and R^2 is the coefficient of determination of the regression equation where each explanatory variable regressed on all the other explanatory variables.

Table C4. Decomposition of the changes in gender wage gap for the US, 1979-1988 vs. 1994-2008

Panel A. Descriptive statistics	1979 vs 1988	1994 vs 2008
Male residual SD*		
year t	0.496	0.546
year t'	0.534	0.578
Mean female residual from male wage regression		
year t	-0.501	-0.316
year t'	-0.359	-0.289
Mean female residual percentile**		
year t	22.028	33.106
year t'	29.082	34.018
Panel B. Decomposition of the change in the gender wage gap		
Change in gender wage gap	-0.138	-0.060
Gender wage gap, year t	0.505	0.270
Gender wage gap, year t'	0.367	0.210
(1) Observed characteristics	-0.011	-0.032
Observed X's effect	-0.002	-0.019
Observed S's effect	-0.009	-0.013
(2) Observed prices	-0.012	-0.014
Observed X prices effect	0.002	-0.002
Observed S prices effect	-0.014	-0.012
(3) Unobserved prices effect	0.026	0.012
(4) Gap effect	-0.141	-0.026

Data source: CPS March Supplements (1980, 1989, 1995 and 2009). Notes: The change in the differential is the change in the male-female log wage differentials between time t (1979 in the second column and 1994 in the third column) and t' (1988 in the second column and 2008 in the third column). *Estimated using male wage regression. **Computed by assigning each women a percentile ranking in the indicated year's residual male wage distribution and calculating the female mean of these percentiles.