Gender Wage Gap Trends in Europe: The Role of Occupational Allocation and Changing Skill Prices*

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Abstract

The aim of this paper is to explore the gender wage gap trends in European labor markets taking a comparative perspective across various countries: Austria, Ireland, Italy, Portugal, Spain and the UK. Using the Occupational Information Network data and the harmonized data for the years 1995-2009 from the European Community Household Panel and European Union Statistics on Income and Living Conditions, we determine the evolution of relative "brain" and "brawn" skill intensity of jobs held by women and men. Then, given the occupational allocation of males and females, we estimate the returns to 'brains" and "brawns" in each year and analyze the trends in returns to those skills. Our results suggest that, despite the increasing over-representation of women in brain skill intensive occupations, returns to "brain" versus "brawn" skills did not change in favor of "brains" between 1995 and 2009 in European labor markets. Our decomposition analysis reveals that the change in worker composition is the major factor that explains the narrowing gender wage gap between 1995 and 2009 in the European labor markets.

Keywords: Gender wage gap, brain skills, brawn skills, decomposition.
JEL Classification: J16, J24, J31, J71.

1 Introduction

Despite decades of equal pay legislations, the gender wage differentials persist in all European labor markets. In 2008 women on average earned 18% less than men per hour

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(Smith, 2010). Moreover, the levels and trends in the gender wage gap varies substantially across European countries. This paper focuses on the cross-country differences in gender wage gap trends, highlighting the role of occupational allocation and changing skill prices on determining the gender wage gap trends.

The gender wage gap is one of the most intensively researched topics in economics. The literature has explored the sources of gender wage differentials to understand the nature and the persistence of the gap. The theories of gender wage gap can be broadly classified as supply-side theories and demand-side theories. According to supply-side theory, the gender wage difference is mainly a consequence of gender differences in human capital investments between men and women. Women are less educated or they study different fields than men which have less access to achieving higher paying jobs, and they have less labor market experience or company-specific skills because of the career interruptions due to marriage or child-care responsibilities (Altonji and Blank, 1999; Becker, 1964; 1968; Polachek and Siebert, 1999) or division of labor in the family (Mincer and Polachek, 1974; Becker 1985). Since women's expected lifetime labor force participation is lower than men, women prefer occupations with higher starting wages but lower returns to experience (Polachek, 1981, Kim and Polachek, 1994). They also prefer to work in occupations with lower wages, but with other preferred characteristics, such as better working conditions or family-friendly working schedules (Filer, 1985).

On the other side, demand-side theories of gender wage gap mainly emphasize the different situation women and men face in the labor market. These differences might arise due to the discrimination by employers (Becker, 1957; Phelps, 1972; Arrow, 1973); or due to the disadvantageous position of women in existing segments of the labor market (Reich et al., 1973; Gordon et al.,1982) or due to the social norms and social networks which form the gender roles, expectations, opportunities and choices of men and women (Marini and Fan, 1997). As a result, women face more difficulties getting hired, getting promoted than men and women end up working in low paid female dominated occupations. Moreover, according to crowding approach, this over-representation of women in a small number of occupations than their male counterparts, results in excess supply of labor and a depression of wages (Bergmann, 1974; England et al., 1988). Therefore gender wage gaps exist.

Traditionally, empirical studies on gender wage differentials have focused on supply side explanations. The decomposition method introduced by Oaxaca (1973) and Blinder (1973) and its extensions have been widely used in the empirical labor economics literature to explore the differentials in human capital investment of men and women within countries. Following Juhn, Murphy, and Pierce (1991) and Katz and Murphy (1992), studies on international differences in gender wage gaps (Blau and Kahn, 1992 and 1996) and on trends in female-male wage differentials (Blau and Kahn, 1994 and 1997) shifted the attention to investigate the relationship between trends in overall wage structure and the gender wage gap. In particular, these studies documented that the change in wage structure in the United States during 1980s, raised overall inequality (Katz and Murphy 1992; Juhn, Murphy and Pierce 1993) and widened the gender wage gap (Blau and Kahn, 1997). The change in the wage structure has been attributed mainly to the technological change, in particular to the developments in computer technology. With the development of computer technologies, a shift in the production technology occurred favoring certain skills by increasing their relative productivity and hence, their relative demand. Thus, the changes in the relative prices of skills led a change in wage structure. However, less attention has been paid to the cross-country differences in gender wage gap trends and changes in relative skill prices. It is important to note that, changing demand for skilled labor will favor occupations that are more intensive in cognitive or brain skills. If women and men are disproportionately allocated to the occupations which require different skills, and if women are over-represented in occupations that are more intensive in "brains", then the gender wage gap would narrow. Moreover, the cross country variation in technological progress would partially explain the cross-country differences in gender wage gap trends.

Given the potential role of occupational allocation and the skill prices, this paper explores the role of changes in composition of jobs held by males and females and the changes in returns to skills on influencing gender wage gap trends in a cross-country perspective. For this purpose, first, we determine the skill requirement of occupations using the data from Occupational Information Network (O*Net). Following the theoretical framework by Galor and Weil (1996) and Welch (2000) and differently from the traditional measures of worker skills such as education and labor market experience, we characterize occupations by two primary attributes, "brains" and "brawns". Initially, we do not assume any comparative advantage of men and women in different skills.[1] Instead, we match the data on brain and brawn skill requirements of occupations with the individual level data from the European Community Household Panel (ECHP, 1995–2001) and European Union Statistics on Income and Living Conditions (EU-SILC, 2004–2009). This matching procedure, allows us to explore the role of trends in skills on the gender wage gap trends from 1995 to 2009 for a set of countries: Austria, Ireland, Italy, Portugal, Spain, and the United Kingdom.

We first analyze the gender wage gap trends in European labor markets between 1995 and 2009. Second, we determine the changes in skill intensity of women and men given their occupational allocations in each country in each year.[2] Then, by estimating the marginal contribution of brain and brawn skills to the wages for each year, we analyze the trends in returns to those skills in the European countries. Our descriptive analysis suggest that, women are over-represented in occupations which are more intensive in "brains" and they are increasingly represented in those occupations, but the returns to brains versus brawns did not change in favor of brains in the European labor markets. Our decomposition results, reveals that the change in worker composition is the major factor that explains the narrowing gender wage gap between 1995 and 2009 in the European labor markets.

Our approach is closely related to the growing literature on the task-based approach of technological change. The task-based view of technological change introduced by Autor, Levy and Murnane (2003) has analyzed the relation between technological change and job skill demands.[3] In this framework, work performed in an occupation is broken

[1]Galor and Weil (1996) argues that women and men have equal quantities of brain skills but men have more brawn skills, while Welch (2000) considers that men are brawn intensive relative to brains, while womens skills are brain intensive relative to brawn.

[2]This allocative process may result from differences in skills of workers, different choices of individuals, or discrimination in the process of recruitment or hiring which is taken as given over the time period of analysis.

[3]See Katz and Autor (1999) and Acemoglu (2002) for a review of earlier studies on the technological

down into routine and non–routine tasks, which are substitutes and complements with computers, respectively. The decline in the price of computer technologies reduced the labor demand for routine tasks and increased labor input for non–routine tasks. Task-based approach has been used to analyze the wage differentials for certain countries. For instance, Peri and Sparber (2009) and Amuedo–Dorantes and de la Rica (2011) use the task-based approach to understand the relation between the task distribution and the wage distribution of native and foreign-born workers, for the US and Spain. On the other hand, the number of studies in the literature which has employed the task based approach to analyze the gender gaps is rather limited. One of these studies is Borghans, ter Weel, and Weinberg (2006). Using data for Germany, the US and the UK, Borghans, ter Weel, and Weinberg (2006) analyze the effect of technological change and innovative work practices on skill requirements of occupations. They show that occupations which require more computer usage and higher extent of team work require more "people" skills. Moreover, women have relatively higher employment rate in occupations which require "people" skills and the increased importance of people skills by the technological change and innovative work practices have raised womens relative employment in those occupations. We complement their findings by showing the increasing representation of women in occupations which require "brain" skills that are potentially becoming more important by technological progress for various European countries. In addition, we analyze the changes in returns to these skills and the impact of these changes on the gender wage gap trends in various countries.

The two empirical papers most closely related to our study are Black and Spitz-Oener (2010) and Bacolod and Blum (2010). Black and Spitz-Oener (2010) study the effect of changes in the tasks performed within occupations on the gender wage gap trends in Germany. Different than ours, their task measures comes from a German dataset, the Qualification and Career Survey and they are self-reported measures of tasks performed within occupations. They find that changes in the relative task and relative price changes together explain more than 40 percent of the narrowing of the gender gap in West Germany (Black and Spitz-Oener, 2006). Moreover, they find that changes in task prices contributed to widening the gender gap in West Germany. Overall, these results are parallel to our findings. However, the magnitude of the effect that Black and Spitz-Oener (2010) predict for West Germany is much higher than ours for other European countries. This difference is potentially due to the differences in the time period of analysis. Black and Spitz-Oener (2010) focus on the changes between 1979 and 1999, while we consider a later period, from 1995 to 2009. suggest that declining relative demand for manual tasks and increasing relative demand for analytic/cognitive tasks play an important role in the change in the gender wage gaps, former in Western Germany and the later in the US labor market.

On the other hand, Bacolod and Blum (2010) analyze the effect of changes in skill prices on the increasing wage inequality and narrowing gender wage gap in the United States during 1968-1990. Similar to our findings for the European labor markets, they find that during this period females were employed in more cognitive- and people-intensive occupations relative to males. However, their results suggest that changes in skill prices contributed to narrowing the gender gap in the US, while our findings for various European countries and the results for West Germany by Black and Spitz-Oener (2010) suggest

progress and its impact on the employment structure.

that changes in skill prices contributed to widening the gender gap in the European labor markets. The diverging dynamics in the US and European labor markets might explain these differences. Indeed, earlier studies using the education as a measure of skill show that the relative demand for skills and wage inequality did not increase as much in Europe as it did in the US between the 1970s and 1990s (Acemoglu, 2002) and the US gender wage gap narrowed faster during the 1980s and 1990s than any other European country (Blau and Kahn, 2000). The theoretical explanations for the differences in the impact of technological change on the wage inequalities in the US and Europe potentially explain the differences between our results and the results for US by Bacolod and Blum (2010). These explanations include the faster increase in relative supply of skills in Europe, the role of European labor market institutions which prevented inequality to rise, and the differences in technical change or openness to international trade (Acemoglu, 2002; Greiner et al., 2004). Instead, we focus on the cross-country differences on the effect of changes in skill composition and in returns to skills on the gender wage gap trends in European countries from 1995 to 2009. For this purpose, the next section provides a brief overview of the female labor market outcomes and institutional setting in Austria, Ireland, Italy, Portugal, Spain and in the UK. Section 3 presents the data sources and describes the construction of the data and concepts used in the analysis. Section 4 presents the gender wage gap trends using graphical techniques. We then explore the underlying mechanism of changes in skills and skill prices effect; trends in intensity of males and females in brain and brawn skills and trends in returns to brain and brawn skills. Section 7 explains the details of the decomposition technique which allows us to break down the changes in the gender wage gap into components and presents our main results using the decomposition of changes in gender wage gap. Finally, Section 8 concludes.

2 European Labor Markets

2.1 Female Labor Market Outcomes

This section briefly summarizes the trends in labor market outcomes for women in the six countries of focus; Austria, Ireland, Italy, Portugal, Spain and the UK.

First, in all six countries, female labor market participation has risen remarkably over the last decades (Figure A.1 of Appendix A). However, the initial levels and the timing of the increase have varied across countries. Basically, one can identify three distinct patterns of female labor force participation: (i) low initial level and sharp rise (in Spain and in Ireland), (ii) high initial level and moderate rise (in Austria, in Portugal and in the UK), and (iii) low initial levels and very small rise (in Italy). Among the countries of focus, the UK and Portugal had the highest female labor force participation in 2009, with a rate more than 55% (Figure A.1 of Appendix A). Ireland, Italy and Spain are the three countries with the lowest female labor force participation rates in the early 1980's. However, over the past two decades, there has been a large increase in female employment in Ireland and in Spain. Austria, Portugal and the UK experienced modest increases in female employment throughout the period, while, in Italy female employment rate remained around 38.4% in 2009.

Second, there has been also a remarkable increase in female educational attainment levels among all countries (OECD, 2011). In 2008, for cohorts aged 45-54, educational attainment level of females was similar to the males, while for cohorts aged 25-34, females were much more educated than their male counterparts (Table A.1 of Appendix A). The difference in higher educational attainment between young females and males ranges from 2 percentage points in Austria to 14 percentage points in Ireland. Tertiary educational attainment levels of young males and females remain below the OECD average in Austria, Italy and Portugal. In Ireland, in Spain and in the UK the educational attainment rates of females and males were either at OECD average or even higher. Moreover, the proportion of younger females (25-34 year-olds) with tertiary educational attainment was much higher relative to older cohorts. Especially in countries where the rates were high (Ireland, Spain and the UK), the differences between two generations are remarkable (Table A.1 of Appendix A).

Despite the above mentioned changes, which most likely have a positive impact on female labor market outcomes, the gender gaps in employment rates persist in all countries, with the gap being lowest in Austria (about 9 percentage points) and considerably high in Italy (about 26 percentage points) in 2009 (Table A.2 of Appendix 2). A significant proportion of the employed females are working in low status jobs which are associated with lower hourly wages (OECD, 1994) and reduced access to occupational benefits (ILO, 1989; OECD, 1994). Relative to their male counterparts, women are more likely to have a temporary employment contract rather than a permanent one. Moreover, they are less likely to achieve managerial and supervisory jobs. The gender gap in managerial positions ranges from 65.6 percentage points in the UK to 73.2 percentage points in Austria (Table A.2 of Appendix 2).

It is worth noting that the gender differentials in labor markets are of increasing concern to policy-makers at both national and European levels. All countries covered by this study have legislation concerning pay discrimination at work. In Italy, Portugal and Spain the constitutions explicitly prohibit the wage discrimination. In addition, in Austria and Ireland, as well as in the UK there are specific laws prohibiting the direct or indirect wage discrimination between men and women.[4] Legislations of this type certainly have an impact on gender wage gaps which will most likely depend on the effectiveness of the legislations enforcement. However women in most of the countries still lag behind men in terms of labor market outcomes (Pissarides et al., 2005).

2.2 Family-Friendly Policies

In addition to legislations prohibiting discrimination at work, policies concerned with reconciling work and family life such as child-care, maternal, paternal and parental leave and wage-setting institutions such as collective bargaining conventions and minimum wage laws also may affect the gender wage gap. This section briefly summarizes the policies and wage-setting institutions of the countries in focus and the potential impacts on the

[4]In Austria, the 1979 Act on Equal Treatment on Men and Women; in Ireland the 1998 Employment Equality Act, repealing the 1974 Anti-Discrimination (Pay) Act and the 1977 Employment Equality Act; in the UK the Equal Pay 1970, as amended by Equal Value Regulations of 1983, and the Sex Discrimination Act of 1976 and 1986. See Soumeli and Nergaard (2002) for a review of legislation in European countries concerning gender discrimination.

gender wage gap.[5]

Child-care and parental leave can affect the relative human capital levels of women which has a direct impact on gender wage gap. Child-care facilities especially for preschool children or all-day childcare arrangements are other tools which particularly affect women. Together with the parental leave schemes, the coverage and availability of affordable child care may decrease the career interruptions of mothers during the years after the birth and hence increase the incentives of employers and women workers to invest in firm-specific training.[6] On the other hand, as discussed by Blau and Kahn (2003), the impact of maternal leave on gender wage gap is ambiguous. Maternal leave schemes may promote gender equality and increase women's earnings by keeping the attachment of working mothers to their job during the period of childbirth and childrearing and hence by increasing the incentives of employers and women workers to invest in firm-specific training. Nevertheless, existence of long maternal leave schemes may have a widening effect on gender wage gap. By long maternity leave women may postpone their return to work and hence get long career interruptions. Even further, existence of such policies may increase the incentives of employers to discriminate in hiring or increase the incidence of withdrawals from the temporary labor force may increase.[7]

All European Union Member States have statutory maternity leave schemes guaranteed by the minimum requirements set out in 1992 by the European directive on maternity leave. However the national schemes vary to a great extend in the length of the leave period; the payment during the parental leave and the flexibility of the scheme (Anxo et al., 2007). In 2008, the average duration of maternity leave was around 19 weeks across the OECD countries (OECD, 2011). Among the countries in focus, Ireland and the UK have substantially longer maternity leave periods, the UK with 52 weeks and Ireland with 42 weeks. However, in both of the countries leave is not paid for the full period. In Italy, the full rate equivalent paid maternity leave duration is 16 weeks out of 20 weeks of total maternal leave period. Women are entitled to 17 weeks leave at full pay in Portugal and 16 weeks in Austria and in Spain (OECD, 2011). There is not much flexibility in maternity leave. For example in Austria and Italy maternal leave is obligatory. There are also few exceptions like Spain, where the maternal leave period can be transferred or shared with fathers without any exceptional circumstances such as death or serious illness applying (Moss, 2011). On the other hand, periods of paternity leave are much shorter than for maternity leave, about four to five weeks on average, and are paid usually on the similar basis as maternal leave while the payment rates for parental leave are often lower than maternity pay (Moss, 2011; OECD, 2011). In 2011, parental leave was unpaid in Ireland, in Spain and in the UK.

In addition to parental leave schemes, countries vary in childcare supports to a great extent. Public spending on childcare including pre-primary school services as a percentage of GDP is highest in the UK at 1.1% of GDP and Ireland at 0.2% (OECD, 2010a). On the other hand, enrollment to pre-school education for children 3-, 4- and 5-year-olds is often heavily subsidized or provided for free in these countries (OECD, 2011). The enrollment rates for this age group of children were highest in Italy and Spain in 2008

[5]See Table A.3 of Appendix A for a summary of family-friendly policies and wage setting institutions.

[6]See Gupta, et. al. 2006 for a summary of empirical results for various countries.

[7]See Schnberg and Ludsteck (2007) for a review of empirical literature on effects of maternal and parental leave schemes on gender wage gaps.

(more than 97% of children) and lowest in Ireland with 56.7% (OECD average: 58.2%). As mentioned before access to affordable formal childcare helps parents and especially women in low income families to participate in paid work. However, by 2007, childcare fees as a percentage of the earnings of an average worker were much higher in the countries of focus, than OECD average (16%), ranging from 8 percentage points difference in the UK to 14% in Spain. Exceptionally in Austria child care fee was below the OECD average, around 9.6% (OECD, 2007).

2.3 Wage Setting Institutions

Besides the family-friendly policies, labor market institutions such as trade unions, collective bargaining arrangements and minimum wage setting mechanisms are key determinants of the wage structure of a country. Previous literature have found that countries where the level of collective bargaining coverage is high and the wage setting system is more centralized, entail less wage inequality and lower gender wage gap (Blau and Kahn, 1996; 2003). The centralized minimum wage has a narrowing effect on the gender wage gap, since it is binding mostly for women than men who remain disproportionately at the lower tail of the wage distribution. Furthermore, the centralized wage setting mechanism decreases the sectoral wage differences, which in turn decreases the gender wage gap associated to the allocation of males and females to different sectors (Blau and Kahn, 2003). On the other hand, for countries where bargaining takes place mainly at the firm level, collective bargaining is the most important factor influencing wage determination within firms. The effect collective bargaining arrangement on gender wage gap highly depends on the unionization rate of female and male workers and the coverage of collective bargaining. For instance, this effect may widen the gender wage gap, if the women are less likely to be union members than men, since the unionized workers wages are higher than their non-unionized counterparts (Felgueroso et al., 2007).

Among the countries in focus, Austria, Italy and Portugal are the countries with high levels of collective bargaining coverage (Fulton, 2011). In Austria, there is no national level minimum wage and minima are set by the sectoral collective agreements. Austria stands at one extreme with the high degree of collective bargaining coverage. About 98%–99% of employees are covered by sectorally agreed minimum wage rates (Broughton, 2009). In Italy, also there is no national minimum wage and industry-wide bargaining takes place at national level with the second-level bargaining at company level. In 2006, the fraction of employees covered by the collective bargaining was about 80% (EIRO, 2010). In Portugal, where a statutory national minimum wage is in place, the national minimum wage is set and uprated by the government (Broughton, 2009). In 2009, 90% of the labor force was covered by collective bargaining which is predominantly taking place at industry level. However after the recent financial crisis, the government started to do changes, which are likely to reduce the proportion of employees covered by collective bargaining like stopping the extension of agreements to employers who were not signatories (Fulton, 2011). The national minimum wage in Spain has been in place since 1969, and is upgraded annually by the government, taking into account the inflation forecasts and after consultation with the social partners. The collective bargaining coverage in Spain is between 60% and 75%, and the most important level of bargaining is the provincial sectoral level. The recent economic crisis also affected the legislations for collective bargaining in Spain. According to new legislation, employers can legally negotiate terms and conditions at company level and agree on those which are worse than in the higher level agreements that cover them (Fulton, 2011). In the other two countries, in Ireland and in the UK, the collective bargaining coverage is taking place at company level and the coverage rates are low (44% in Ireland and 33% in the UK).

3 Data, Concepts and Descriptive Statistics

This study brings together the information provided by three data sources. Individual level data on employment and wages comes from two different sources European Community Household Panel (ECHP) for the years from 1995 to 2001 and European Union Statistics on Income and Living Conditions (EU-SILC) for the years between 2004 and 2009. Data on occupational skill requirements are provided by the Occupational Information Network (O*Net). The following two subsections briefly describe these sources and sample restrictions.

3.1 Individual Level Data

Individual level data on wages and other labor market variables comes from two different sources. Currently, there is no single data source to study the long term dynamics of the wage structure in Europe. For this reason we used the harmonized data from European Community Household Panel (hereinafter, ECHP) from 1995 to 2001, and the European Union Statistics on Income and Living Conditions (hereinafter, EU-SILC) from 2004 to 2009.[8]

ECHP is a standardized annual longitudinal survey carried out in the European Union countries from 1994 to 2001 which includes detailed information on demographics, labor force behavior, income including wages, education and training, health and migration and also supplementary information at the country level on purchasing power parity (PPP), consumer price index (CPI) and sampling weights.[9] Following concerns about the comparability and timeliness of data across the European Community, ECHP was replaced after 2002 with EU-SILC. Although the contents of these two surveys are quite similar, there are some important differences. First, EU-SILC focuses on income and living conditions, while ECHP has a wider focus on economic and household situation. Second, ECHP is a harmonized survey while EU-SILC is rather a common framework (it is defined as a harmonized lists of target variables). Third, ECHP is an eight years pure panel while EU-SILC is a four years rotational panel which also provides a cross-sectional component that is nationally representative. Despite these differences, harmonizing some of the variables of the two datasets is possible.[10]

Our key variable is gross hourly wage constructed by dividing gross monthly wages by monthly hours worked in the main job. Gross monthly wage is available in ECHP for Ireland, Italy, Portugal, Spain and the UK from 1994 to 2001 and for Austria from

[8]See Appendix B for an overview of these data sets.

[9]See Peracchi (2002) for an overview of ECHP data.

[10]Recently Goos, Manning and Salomons (2009 and 2011) make use of wages from these two surveys to investigate job polarization trends in Europe.

1995 onwards. EU-SILC provides current gross monthly wage for Austria, Ireland, Italy, Portugal and Spain from 2004 to 2009 and for the UK from 2005 onwards. Hence we restrict our analysis to the these six countries which provide complete information on monthly wages and hours in both surveys from 1995 to 2009. Wages are converted in 2001 PPP units using the purchasing power parity (PPP) exchange rates and then deflated by using the harmonized consumer price index (HCPI=2001).[11] Finally, wage observations ten times greater than the 99th percentile and ten times lower than the 1th percentile of the country wage distributions are excluded from the sample.

In addition, ECHP and EU-SILC include several variables on the labor market characteristics of individuals such as marital status, part-time employment, type of employment contract, occupation and educational attainment. The occupation in both surveys is defined using the International Standard Classification of Occupations (hereinafter, ISCO-88) and codded at the two-digit level. A common problem of education variable, the comparability between countries due to the differences in systems of educational qualifications, is not presence in ECHP and EU-SILC. The education variable is harmonized by using the International Standard Classification of Education (hereinafter, ISCED) categories. High educational qualifications are defined as ISCED categories 5-7, and include recognized third level education. Secondary education is defined by ISCED categories 3 and 4, and includes all second stage of secondary level education. Low education is defined as having no qualifications or only qualifications below the secondary education level, and corresponds to ISCED categories 0-2.

Actual labor market experience is another important variable for the purposes of this study. EU-SILC, provides the exact number of years spent in paid work with two exceptions; for Ireland for the initial three waves and UK over the entire period. For Ireland and UK the missing information on experience in EU-SILC is recovered using the years passed after the highest level of education was attained. However, ECHP lacks the information on actual labor market experience. However it provides the age when the individual completed the highest education attained and also the age when she/he started the working life.[12] Moreover, we have information about the number of months of continuous unemployment before current job, even if the whole unemployment history is missing. Using these variables we generate a proxy for labor market experience. To proceed more 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). We computed our measure for labor market experience for individuals who completed their education earlier than starting to the working life (if $y_s >= y_w$) as $exp = y_t - y_w$ and for the ones who started the working life before completing their highest education degree (if $y_s > y_w$) as $exp = y_t - y_s$. Then, we partially corrected our measure for labor market experience, by subtracting the continuous months of unemployment before current job ($exp^* = exp - y_u$).

Finally, the sample is restricted to individuals of working age, between 16 and 64 years

[11]Both surveys include supplementary information on PPP exchange rates and HCPI is extracted from OECD Main Indicators database.

[12]In ECHP age is top-coded at 85 years in wave 1, 86 years in wave 2, and so on, for all countries, whilst age at first job is top coded for all countries and waves at 60 years. As we are mostly concerned with working age population, aged 16-64, these top-coding rules are relatively unimportant.

old, working at least 15 hours per week with valid observations on all the variables used in the wage equations. As suggested by Commission of the European Communities, gender wage gap "ought to be based on data covering the whole economy, including all sectors and firm sizes, including possibly also those working less than 15 hours per week" (CEC, 2003). However, the restriction of working at least 15 hours per week is necessary because of the nature of ECHP, since ECHP does not distinguish individuals regularly working less than 15 hours from those out-of the labor force in the first two waves.[13]

3.2 Data on Skill Requirements of Occupations

The Occupational Information Network (hereinafter, O*Net) database is the most well known source for the recent information on occupations in the US labor market.[14] O*NET, is a database developed by the US Department of Labor which provides detailed information about worker and job characteristics for more than 1110 occupations in the US. It is a replacement for the Dictionary of Occupational Titles (DOT) which has been extensively used in earlier research (Autor, Levy and Murnane, 2003; Goos and Manning, 2007; Bacolod and Blum, 2010). Existing studies use DOT or O*Net for three key applications. Autor, Levy and Murnane (2003) and Goos, Manning and Salomons (2009 and 2011) used the occupational information to asses the effect of technical change on skill demands and on job polarization for distinguishing routine from non-routine tasks. More recent papers on labor market outcomes of native and foreign born workers use the DOT or O*Net information to distinguish communication tasks from manual tasks to analyze the effect of immigration on native wages (Amuedo-Dorantes and de la Rica, 2011; Peri and Sparber, 2009) and to determine the role of labor-market competition on attitudes towards immigrants (Ortega and Polavieja, 2012). Occupational information data has been also used in studies on gender gaps in labor markets. Borghans, ter Weel and Weinberg (2006) use occupational information from DOT to show the relative intensity of women people skills which are becoming more important over time by technological and organizational changes. Bacolod and Blum (2010) also make use of DOT data on occupations to understand the role of skill prices on increasing wage inequality and closing gender wage gap in the US labor market.

O*NET organizes the job information into a structured system of six dimensions: worker characteristics, worker requirements, experience requirements, occupational requirements, labor market characteristics, and occupation-specific information. Each domain includes a set of measurable descriptors reflecting the relative importance of the corresponding worker attribute or occupational requirement, including worker abilities. O*Net database includes fifty-two measures related to worker abilities which are defined as "enduring attributes of the individual that influence performance" and clusters these measures under several subsets, including their detailed description.

For example, worker abilities domain includes a subset called cognitive abilities defined by O*Net as "the abilities that influence the acquisition and application of knowledge in problem solving". Cognitive abilities consists of seven more subsets including quantitative

[13]Tables for descriptive statistics of the final sample for each country in 1995 and 2009 can be found in Appendix B.

[14]For a description of the O*NET data see Appendix B.

abilities – “abilities that influence the solution of problems involving mathematical relationships”. Under this subset there exists two O*Net measures mathematical reasoning – “the ability to choose the right mathematical methods or formulas to solve a problem” and number facility – “the ability to add, subtract, multiply, or divide quickly and correctly”. It is common in the literature to reduce the large number of descriptors to a relevant subset using textual definitions.[15] We also use a subset of the descriptors classified under worker abilities – twenty one different measures of cognitive ability intensity, ten measures of psycho-motor ability intensity and nine measures of physical ability intensity (Table C.1 of the Appendix C provides the list and the description of the variables used, organized by brain and brawn skill type).

To construct two broad skills, we used all the descriptors classified under cognitive abilities to construct “brain” skills, and the descriptor classified under psycho-motor and physical abilities to construct “brawn” skills. The remaining O*NET ability variables largely pertain to sensory dimension and we do not include them in our analysis. We excluded the descriptors measuring sensory abilities mainly for two reasons. First, sensory abilities include descriptors that are not clearly being classified under one of the two sets (“brains” and “brawns”) according to their textual definitions. Second, they are related with some measures of cognitive abilities and at the same time with psycho-motor and physical abilities which prevents the clear classification of skills.[16] The list of O*Net descriptors under these two clusters are presented in Table C.1 of the Appendix C. All variables used in the analysis have the importance scale where the occupational experts rank each descriptor as not important at all (1), somewhat important (2), important (3), very important (4) or extremely important (5). The following two subsections describes in detail the procedures followed to construct the skill requirements of occupations and steps of matching the occupation-level skill information with individual-level data.

3.2.1 Constructing Skill Requirements of Occupations Using O*Net Descriptors

To construct skill requirements of occupations, first, we manually converted the 2010 Standard Occupational Code (SOC) used in the O*NET data to ISCO-88 codes.[17] Then, since our individual level data provide occupation information at aggregate level (eighteen occupation categories), we take the weighted average of the descriptor values for the detailed level occupations under the broad title, where the weights are percentage of workers employed in US labor market in 2001.

As pointed out by the early research, O*Net descriptor values range from one to five, but the score of each descriptor varies considerably across occupations. Peri and Sparber (2009) and Amuedo-Dorantes and de la Rica (2011) overcome this problem by rescaling the measures to reflect the relative importance of each skill among all occupations. Following

[15]See Amuedo-Dorantes and de la Rica, 2011; Autor, Levy and Murnane, 2003; Bacolod and Blum, 2010; Goos, Manning and Salomons, 2009; Peri and Sparber, 2009.

[16]We checked the consistency of this classification using principal component analysis performed among all set of descriptors under worker abilities title. Informed by this analysis, we categorized cognitive ability measures as brains and psycho-motor abilities together with physical abilities as brawns. The results of the principle component analysis performed among all set of attributes are available upon request. The details of the principle component analysis technique can be found in Appendix D.

[17]See Appendix C for the details of matching procedure.

their methodology, we rescaled the O*Net descriptors. To proceed more formally let s_{ij} be the value of skill descriptor i for occupation j where $j = 1, 2, ...18$; and the maximum and minimum value of the descriptor s_i among occupations be $\overline{s_i}$ and $\underline{s_i}$. We rescaled each skill descriptor value as the following: $s^*_{ij} = (s_{ij} - \underline{s_i})/(\overline{s_i} - \underline{s_i})$. Using the rescaled descriptor values, s^*_{ij}, we then construct the measures of brain and brawn skills. To do so, we took the simple average of corresponding set of descriptors' rescaled values. Table 1 displays the occupations under the broad classification, as well as the brain and brawn skill summary measures for each of the occupations.

Table 1: Brain and brawn skill intensity of occupations

Occupation	Average of Rescaled Values			Occupation
code	Brains	Brawns	Brains/Brawns	title
1112	0.74	0.16	4.68	Legislators, senior officials, corporate managers
1300	0.78	0.10	7.94	Managers of small enterprises
2122	0.86	0.33	2.59	Physical, mathematical, engineering, life science, health professionals
2300	0.76	0.08	9.56	Teaching professionals
2400	0.71	0.11	6.24	Other professionals
3132	0.65	0.51	1.27	Physical, engineering, life science, health associate professionals
3334	0.52	0.07	7.59	Teaching and other associate professionals
4142	0.42	0.22	1.97	Office and customer services clerks
5100	0.38	0.62	0.60	Personal and protective services workers
5200	0.45	0.33	1.36	Models, salespersons and demonstrators
6100	0.28	0.80	0.35	Skilled agricultural and fishery workers
7174	0.49	0.87	0.56	Extraction, building, other craft and related trades workers
7273	0.47	0.78	0.60	Metal, machinery, precision, handicraft, printing and related trades workers
8183	0.47	0.83	0.56	Stationary-plant and related operators, drivers and mobile-plant operators
8200	0.32	0.64	0.50	Machine operators and assemblers
9100	0.02	0.53	0.03	Sales and services elementary occupations
9200	0.51	0.78	0.65	Agricultural, fishery and related laborers
9300	0.15	0.74	0.20	Laborers in mining, construction,manufacturing and transport
Mean	0.50	0.47	2.63	
Std. dev.	0.23	0.30	3.12	
Pearson correlation coefficient	-0.58			

Note: Occupation codes are based on regrouped (group B) classification of ECHP data. If the occupations are regrouped, the first and the last two digits of the occupation code corresponds to the 2-digit ISCO-88 classification of occupations.

As presented in Table 1, occupations at the top of the brain skill measure distribution are legislators, senior officials and corporate managers, managers of small enterprises and professionals. At the bottom of the brain skill distribution, there are teaching professionals and associated professionals. Teaching professionals and associated professionals are also relatively more brain intensive than brawn skills. Occupations at the top of the brawn skill distribution are mainly blue-collar workers and laborers (in agricultural, fishery, mining, extraction, construction, manufacturing and transport). Sales and services elementary jobs have the lowest relative brain intensity (brains to brawns ratio is only 0.2).

3.2.2 Matching Skill Requirements of Occupations with Data on Individuals

To examine the skill intensity of jobs held by women and men, and returns to these skills, we merge our constructed skill measures with our individual level data under the assumption that workers satisfy the minimum skill requirements of the occupations they are employed in. It is important to note that matching O*Net data with European data relies on the assumption that the occupations in the US and in Europe being examined herein are not different with regards to their skill requirements.[18] On the other hand, since there is no time variation in O*Net, the variation in skills comes only from occupational differences. Our results are valid only if the skill composition within occupations is constant over time. Throughout a long period, some skills might become idle for certain occupations possible due to change in the task content of occupations by technological progress. However, using DOT (earlier version of O*Net) Goos and Manning (2007) show that most of the overall changes in task composition of occupations in US labor market happened between occupations not within occupations. Autor and Handel (2009) also provide evidence on the dominance of occupation as a predictor for the variation in the task measures using the individual level Princeton Data Improvement Initiative. Given the results of previous studies and considering the relatively recent and short length of our individual level data (from 1995 to 2009), it is reasonable to assume that any kind of progression might affect the distribution of skills and skill prices rather than the skill content of the occupations.

4 Trends in the Gender Wage Gaps

In this section, we start to present our descriptive analysis using the matched data set. In this section, we explore the changes in gender wage gap in Austria, Ireland, Italy. Portugal, Spain and in the UK. For this purpose, the gender wage gap is determined by estimating the following wage regression:

$$\ln Wage = \beta_1 + \beta_2 Female + u \tag{1}$$

where the logarithm of gross hourly wages is regressed on a female dummy (that takes 1 for females and 0 for males) for each country at each year without any additional controls. We call the coefficient estimate of the female dummy in this specification *raw gender wage gap*, or in short raw gap. A negative and a significant coefficient estimate implies, existence of the gender wage gap to the detriment of women. The lower the coefficient is, the more disadvantageous women are.

The estimated coefficients and their 95% confidence intervals are presented in Figure 1.[19] The vertical axis of the figure corresponds to the percentage difference between females' and males' average log hourly wages. For example, in 1995 the coefficient estimate for female dummy is around -0.27 for Austria, implying that, in 1995 females were on average earning around 24 percent less than their male counterparts.

As Figure 1 shows, all coefficient estimates are negative and significant (except for Portugal in 2000 and for Ireland in 2009 where the coefficient estimates are insignificant) showing the persistence of gender wage gaps in the European labor markets. Moreover, on

[18] We acknowledge the convention practice in the literature on matching occupational skill requirements of the US labor market with European datasets. See Amuedo-Dorantes and de la Rica (2011) for Spain; Ortega and Polavieja (2009) for 25 European countries to analyze the task specialization of immigrants and Goos, Manning and Salomons (2009, 2011) for analyzing the job polarization in 16 European countries.

[19] The coefficient estimates for the initial and final years (1995 and 2009) can be found in Table E.1 of Appendix E. The full set of estimation results for all the years are available upon request.

average the raw gap narrowed in all countries from 1995 to 2009. If countries compared in raw gender wage gap levels and trends, countries show mainly four patterns: (i) high initial levels and a moderate decline (Austria and UK); (ii) high initial levels and a sharp decline (Ireland); (iii) moderate initial levels and a slight decline (Portugal and Spain); and (iv) low initial levels and a slight decline (Italy). The sharpest decline in the raw gender wage gap experienced in Ireland between 1995 and 2009 with around 15.6 percentage points decrease in the gap.

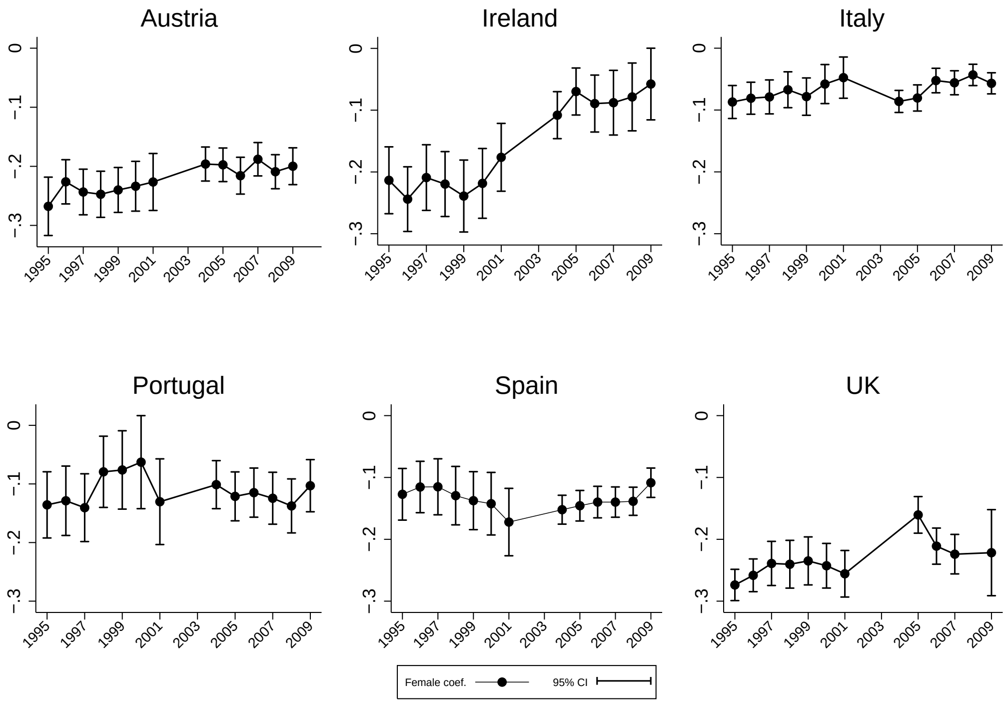

Figure 1: Raw Gender Wage Gap: 1995-2009

The estimates for the raw gender wage gap presented in Figure 1, however, does not take into account neither the gender differences in individual and labor market characteristics nor the changes in these differences over time. The narrowing raw gap can be attributed to many factors including the changes in skills and returns to these skills which are further investigated in the following two sections.

5 Trends in Skill Intensity of Females and Males

In this section, we investigate the evolution of skill intensity of jobs that are held by men and women given the occupational allocations of females and males. Figure 2 illustrates these patterns between 1995 and 2009, by showing the average brain and brawn skill intensity of men and women using the matched data set.

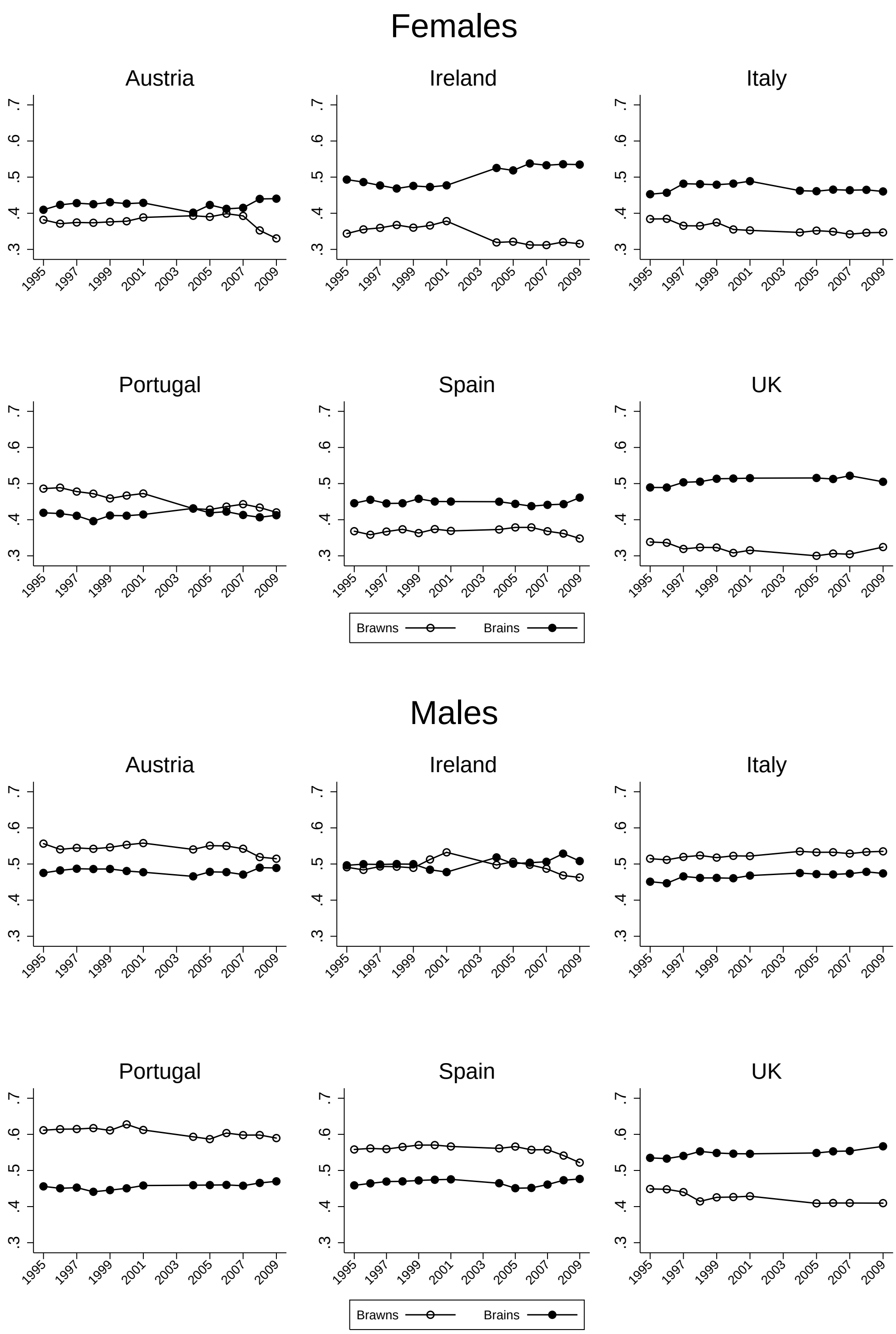

Figure 2: Female and male intensity in brain and brawn skills: 1995-2009

The results presented in Figure 2 reveal the over-representation of females in occupations that are more intensive in "brains", except in Portugal where women were working in brawn intensive occupations at the beginning of the period. In Portugal, female workers increased their representation in brain intensive occupations only after 2000s. In contrast, males work in occupations that are more intensive in "brawns", except in the UK and in recent two years in Ireland where males were also over-represented in brain intensive occupations. For example, in Austria women were employed in occupations with an average brain skill requirement of 0.41 in 1995 (equivalent to the brain skill requirement of an office and customer service clerk) and an average brawn skill requirement of 0.38. In the same year, men were employed in occupations with an average brawn skill requirement of 0.56 (equivalent to the brawn skill requirement of a machine operator) and in occupations require 0.47 brain skill, on average. By 2009, women appear to be catching up to men in terms of brain skills. These results are consistent with the argument of Welch (2000) that women are more intensive in "brains" than men. For example, Bacolod and Blum (2010) show increasing over-representation of females in occupations that are more cognitive skill intensive than men for the US labor market. Black and Spitz-Oener (2010) also find evidence on women to be catching up to men in terms of analytical and interactive skills in West Germany.

One clear result that emerges from Figure 2 is the change in skill intensities of women and men. Over the period, the brawn skill intensity of occupations either declined or remained stable for both genders, while the brain intensities of males and females increased. A common feature for all the countries, except Spain and the UK is the changes in skill intensities being larger for women than for men. In Spain, the intensity of males and females in brain skills show similar patterns, while in the UK males increased their employment in brain intensive occupations and decreased their intensity in brawn skills more than females.

6 Trends in Returns to Skills

6.1 Empirical Specification

In this section, we focus on the evolution of returns to brain and brawn skills in the European labor markets between 1995 and 2009 using the hedonic price model. For this purpose, we specify the empirical model as the following:

$$\begin{aligned} \ln Wage &= \beta_1 + \beta_2 Female + \beta_3 Edu_2 + \beta_4 Edu_3 + \\ &+ \beta_5 Exp + \beta_6 Exp^2 + \beta_7 Brains + \beta_8 Brawns + u \end{aligned} \quad (2)$$

where $\ln Wage$ is logarithm of gross hourly wages. $Female$ is the gender dummy that takes a value 1 for females and 0 for males, as before. Edu_2 and Edu_3 are dummies for secondary and higher levels of educational attainment leaving the low level of educational attainment as the omitted category. Finally Exp is the proxy for labor market experience described in Section 3.1. By hedonic price model, in this setting we assume that occupations are described by their bundle of skills, "brains" and "brawns", and there is no market for skills since they can not be sold separately. Hence, the prices of these skills are not observed independently. Then, the ordinary least squares (OLS) estimates for the skill coefficients in Equation 2 are interpreted as the marginal contributions of "brains" ($\partial \ln Wage/\partial Brains$) and "brawns" ($\partial \ln Wage/\partial Brawns$) to the logarithm of hourly wages. It is worth noting that, since our skill measures do not vary by worker within occupations, we dealt with the problem of estimating the effects of aggregate variables on individual outcomes (Moulton, 1990) by clustering the standard errors at occupation level.

An additional concern might arise due to the selectivity bias, since female labor force participation rates have changed considerably over time (Heckman, 1979). The sign of the bias is ex-ante unpredictable, since the selected group might be positively or negatively selected in terms of their unobserved characteristics (Blau and Beller, 1988; Blau and Kahn, 1997). In the case of positive selection, the coefficient estimates would be biased upwards and downwards in the case of negative selection. Selectivity bias correction (Heckman, 1979) is a common approach to overcome this problem because of its simplicity (Neuman and Oaxaca, 2004). We do not employ the selection correction here. One reason for this is the general concern for the lack of robustness and the distributional assumptions of this approach (Manski, 1989). On the other hand, selectivity bias may not be present only with respect to labor force participation but also with respect to occupational allocation. However, the fundamental ambiguities may arise in the decomposition analysis even sample selection model is correctly identified due to the gender differences in the subcomponents of the selection term. The identification problem in wage decomposition analysis with selectivity corrected wage equations has been pointed out by Neuman and Oaxaca (2004). As Neuman and Oaxaca (2004) argue, it is not clear how to interpret the selection term in wage decomposition and based on the objectives and assumptions the selection component can be regarded in the overall decomposition in several ways. For these reasons we do not employ the selection correction. Moreover, in our decomposition analysis which is described in Section 7, considering the stable labor force participation rates of males, we employ a parametrization based on male's wage equation in the decomposition analysis which would mitigate this problem (Blau and Kahn, 1997).

6.2 Returns to Skills

In this subsection, we present the estimated marginal contributions of 'brains" and "brawns" to the log hourly wages. Figure 3 graphically presents the coefficient estimates for β_6 and β_7 in Equation 2 and their 95% confidence interval.

We report the complete set of parameter estimates for the initial and final years in Table E.2 of the Appendix E.[20] Females on average earn less than their male counterparts even after controlling for brain and brawn skills and for the relevant labor market characteristics. The secondary school graduates on average earn more than the workers who completed primary education and higher school graduates on average earn even more than primary school graduates in all countries over the entire period. Labor market experience has an increasing and concave effect on wages. Since the estimated coefficients for other controls have the expected patterns of sign and significance, from now on we focus on the estimated marginal contributions of brain and brawn skills.

As presented in Figure 3, brain skills were positively and significantly valued in all the

[20] The complete set of estimation results for all the years are available upon the request.

labor market throughout the period, while the marginal contribution of brawn skills to the logarithm of hourly wages was always negative. For example, for Austria, the brains' coefficient estimate is 0.58 in 1995. The standard deviation of the brain skill measure is around 0.2 (See Table 1). If we rank the occupations according to their brain skill requirements, the average difference in brain skill requirement between two consecutive positions in the occupational ranking is 0.05, which is equal to 1/4 standard deviation difference in brain skills. Thus, average increase in brain skill requirements of occupations (1/4 standard deviation increase) is associated with 2.9% increase in hourly wages, such as going from having the brain skills required to be a protective service worker to having the "brains" required to be an office or service clerk.

Similarly, if we rank the occupations according to their brawn skill requirements, again the average difference in brawn skill requirement between two consecutive positions implies, on average, 0.05 change in brawn skill measure which corresponds to a 1/6 standard deviation change in brawn skill requirement (standard deviation of brawn skills is 0.3 as shown in Table 1). For example, for Austria, the coefficient estimate for "brawns" is about -0.30 in 1995. Thus, average difference in brawn skills across occupations is associated with on average 1.5% change in hourly wages. In this case, a change in occupation associated with a 1/6 standard deviation increase in brawn skill requirements, such as going from having the brawn skills required to be a senior official to having the brawn skills required to be an office clerk, was associated with a 1.5 percent decrease in wages.

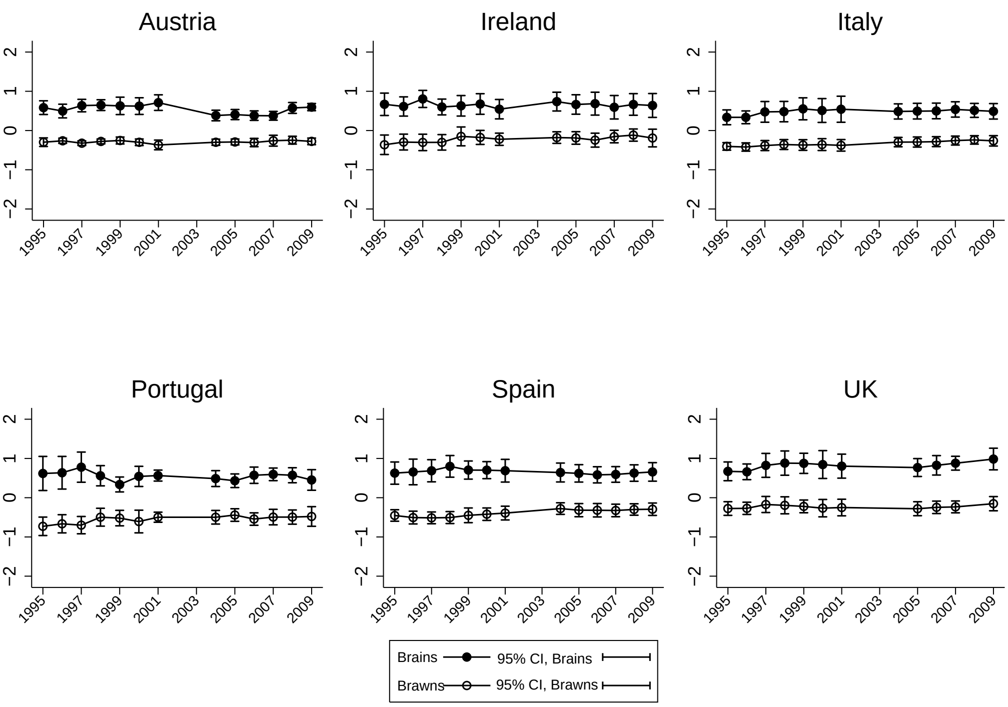

Figure 3: Marginal contribution of brains and brawns to log hourly wages: 1995-2009

The estimated marginal contributions of "brains" and "brawns" are quite similar across countries. One of the most striking features of country figures emerges in the pattern of these returns. The returns to "brains" versus "brawns" did not change in favor of "brains" over the period of analysis in the European labor markets. This result contradicts with the findings of the only study that is comparable to ours, Bacolod and Blum (2010) for the US labor market. Bacolod and Blum (2010) focus on the changes in returns to certain skills during 1968-1990 and show that the returns to cognitive and people skills more than doubled during this period in the US, and returns to motor skills declined by 60 percent while the return to physical strength did not change. However, our results suggest that, European labor markets did not experience such a change in returns to "brains" and "brawns".

There is no other study, as far as we know, that investigates the recent changes in relative returns to skills. However, earlier studies using traditional measures of worker skills, such as educational attinment or occupational classification, show that significant relative demand shifts did not change the relative wages for skilled labor as much in European countries such as France (Katz et al., 1995) and Germany (Abraham and Houseman, 1995) as it did in the US between the 1970s and 1990s. Katz, Loveman, and Blanchflower (1995) using non-manual/manual classification of occupations show that the non-manual/manual wage ratio did not change significantly neither for males nor for females between 1967 and 1987 in France, despite there were substantial employment declines. Contrary, in the same period a dramatic expansion observed in non-manual/manual differentials in the US and Britain. Katz et al. (1995) suggest that in France the minimum wage and collective bargaining coverage might prevent the skill differentials to expand. Similarly, Abraham and Houseman (1995) find little evidence in widening wage differentials across blue- and white-color workers and show the constant differentials across education groups in Germany between 1964 and 1989. They claim that differences in wage-setting institutions in the US and Germany might be a potential explanation for the different trends in wage structures. On the other hand, Bertola and Ichino (1995) emphasize that the same dynamics during the 1980s might contributed to increase wage dispersion in the US and unemployment in Europe.

6.3 Robustness Checks

We have carried out a range of robustness tests, pushing the basic analysis further in several directions. Our first check for robustness focuses on the empirical specification. The empirical specification that we consider, excluding the brain and brawn skill measures, is simple but fairly standard in the literature (Blau and Kahn, 1997; Willis 1986). As a robustness check, we expanded the specification by including other labor market variables. The expanded specification is defined as the following:

$$\begin{aligned} \ln Wage &= \beta_1 + \beta_2 Female + \beta_3 Edu_2 + \beta_4 Edu_3 + \\ &+ \beta_5 Exp + \beta_6 Exp^2 + \beta_7 Brains + \beta_8 Brawns + \\ &+ \beta_9 Permanent + \beta_{10} Full-time + \beta_{11} Married + u \end{aligned} \tag{3}$$

The additional variables include type of employment contract, full-time employment and marital status which maybe to some degree endogenous.[21] However, the main patterns in

[21]The estimation results of this specification for the initial and the final years (1995 and 2009) are presented in Table E.3 in Appendix E.

marginal contribution of "brains" and "brawns" to the wages hold when we use expanded model to estimate skill prices.

The next issue relates to the fact that, the estimation of wage equation including brain and brawn skills simultaneously might exhibit collinearity. As presented in Table 1, brain and brawn skill measures are negatively correlated. The existence of collinearity inflates the variances of the parameter estimates and produces parameter estimates of the "incorrect sign" and of implausible magnitude (Greene, 1993). Taking into account this concern, we computed the variance inflation factor which is a collinearity diagnostic statistics that based on the proportion of variance in the each independent variable that is not related to the other independent variables in the model. Conventionally, a variance inflation factor of ten have been used as rule of thumb to indicate serious multicollinearity (Kennedy, 1992; Hair et al., 1995). The variance inflation factor for each variable is below the rule of thumb ten. Table E2 of Appendix E reports the mean variance inflation factor values for each regression. For a further investigation of the issue, we estimated an alternative specification. This alternative specification is the following:

$$\begin{aligned} \ln Wage &= \beta_1 + \beta_2 Female + \beta_3 Edu_2 + \beta_4 Edu_3 + \\ &+ \beta_5 Exp + \beta_6 Exp^2 + \beta_7 Brains/Brawns + u \end{aligned} \tag{4}$$

which includes only the ratio of brain to brawn skill measure. In this case, the coefficient estimate for brain to brawn ratio, β_7, reflects the marginal contribution of working in an occupation relatively more brain intensive than brawn skill. The full set of coefficient estimates for the initial and the final years are presented in Table E.4 of Appendix E. Once again, the estimation of this specification give positive and significant coefficient estimates for the brain to brawn ratio implying a positive return of working in a relatively brain intensive occupation. However, similar to the marginal contributions of "brains" and "brawns", returns to brains to brawns ratio is stable over the period of aanalysis in all countries.

Next, we examine whether the construction process of skill measures affects the estimation results. For this purpose, we employed a different technique, Principle Component Analysis to construct skill measures instead of using the average of rescaled values. Principle Component Analysis is a data reduction technique which maximizes the amount of variation of the large number of variables explained by a smaller number of components (Jolliffe, 1986) and has been commonly used in the literature to construct measures from DOT or O*Net data (Autor, Levy and Murnane, 2003; Bacolod and Blum, 2010; Goos, Manning and Salomons, 2009; Ortega and Polavieja, 2012).[22] Using the brain and brawn skill measures constructed via Principle Component Analysis, we determined the skill intensity of jobs held by females and males and re-estimate the empirical model specified in Equation 2. The skill measures constructed by the Principle Component Analysis are unit free as our skill measures, but note that the scale of measurement in both technique is different.[23] Table E.5 in Appendix E provides the estimate of the wage regression specified in Equation 2 using the skill measures constructed via Principle Component Analysis. A

[22]See Appendix D for a brief explanation of the technique and the procedure followed to construct skill measures using this method.

[23]Summary statistics of brain and brawn skills constructed by Principle Component Analysis can be found in Appendix D.

comparison of the returns to skills using these new measures of skills with the estimation results discussed in the previous section shows that construction process of skill measures does not alter our results.[24]

7 Decomposition of Changes in The Gender Wage Gap

So far, we have dealt with the descriptive analysis to explore the gender wage gap trends, changes in skill intensity of females and males, and trends in returns to brain and brawn skills. Now, we turn our attention to decomposition of changes in gender wage gap and the contribution of changes in skill composition and returns to skills to the gender wage gap trends. In the following two subsections, we describe the decomposition technique and present the results of the decomposition of the changes in the gender wage gap in Austria, Ireland, Italy, Portugal, Spain and in the UK.

7.1 Analytical Framework

To quantify the contribution of each of the various factors thought to affect the changes in gender wage gap we use a decomposition technique developed by Juhn, Murphy, Pierce (1991), hereafter JMP. The JMP decomposition can be described as follows. Given the consistent estimates of the parameters of interest, let the predictions of females (f) and males (m) wages at time t to be:

$$\widehat{lnW}_t^f = X_t^f \hat{\beta}_t^f \tag{5}$$
$$\widehat{lnW}_t^m = X_t^m \hat{\beta}_t^m \tag{6}$$

where W_t is the vector of hourly gross wage for individuals, at time t. X_t is the matrix of relevant labor market characteristics (education, labor market experience, brain and brawn skills assigned to individuals given their occupational allocation). Following the seminal work by Juhn, Murphy and Pierce (1991), for men and women three hypothetical wage distributions can be derived using:

$$\hat{\epsilon}_t^f = lnW_t^f - \widehat{lnW}_t^f \tag{7}$$
$$\hat{\epsilon}_t^m = lnW_t^m - \widehat{lnW}_t^m \tag{8}$$

and $\hat{\epsilon}_t^{(f)}$; the assigned residuals for each female worker based on the actual percentile in the females' residual distribution derived from equation (4) and the male residual

[24] Using skill measures constructed with another process produces negligible changes in the estimated coefficients. For example, the coefficient estimate for brain skills using the measures constructed by Principle Component Analysis is around 0.14, again for Austria in 1995. In this case, the standard deviation of brain skill measure is one by construction (See Table D.2 in Appendix D). Then one standard deviation increase in brain skills is associated with 14% increase in hourly wages. If we again rank the occupations according their brain skill requirements, a change in occupation implies on average 0.2 increase in brain skill measure, i.e. 1/5 standard deviation increase in brain skills. This change (1/5 standard deviation increase) is associated with 2.8% increase in hourly wages which was associated with 2.9% increase in our main estimations. A similar comparison can be done for the rest of the coefficients.

distribution derived from equation (5). If competitive prices are assumed to be equal to prices estimated from the male wage regression, for women and men three separate hypothetical wage distributions can be derived:

$$\begin{aligned}\widehat{lnW}_t^{1f} &= X_t^f \hat{\beta}_t^m + \hat{\epsilon}_t^{(f)} \\ \widehat{lnW}_t^{2f} &= X_t^f \hat{\beta}_t^f + \hat{\epsilon}_t^{(f)} \\ \widehat{lnW}_t^{3f} &= X_t^f \hat{\beta}_t^f + \hat{\epsilon}_t^f \end{aligned} \tag{9}$$

and,

$$\widehat{lnW}_t^{1m} = \widehat{lnW}_t^{2m} = \widehat{lnW}_t^{3m} \tag{10}$$

where $\widehat{lnW}_t^3$ replicates the true log wage distribution.[25] Using these three hypothetical distributions, the average male-female wage differential can be written as the following:

$$\begin{aligned}\triangle w^1 &= \widehat{lnW}_t^{1m} - \widehat{lnW^{1f}}_t = (X_t^m - X_t^f)\hat{\beta}_t^m \\ \triangle w^2 &= \widehat{lnW}_t^{2m} - \widehat{lnW^{2f}}_t = (X_t^m \hat{\beta}_t^m - X_t^f \hat{\beta}_t^f) \\ \triangle w^3 &= \widehat{lnW}_t^{3m} - \widehat{lnW^{3f}}_t = (X_t^m \hat{\beta}_t^m - X_t^f \hat{\beta}_t^f) + (\hat{\epsilon}_t^m - \hat{\epsilon}_t^f)\end{aligned}$$

and hence;

$$\triangle w^3 = \triangle w^1 + (\triangle w^2 - \triangle w^1) + (\triangle w^3 - \triangle w^2) \tag{11}$$

Note that $\triangle w^3$ is the difference between the true log wage distributions of males and females, that is the average gender wage gap. Hence, using Equation (10) the average gender wage gap at time t can be rewritten as:

$$\begin{aligned}\Delta\overline{lnW}_t &= \overline{lnW}^m{}_t - \overline{lnW}^f{}_t \qquad (12) \\ &= (\overline{X}_t^m - \overline{X}_t^f)\hat{\beta}_t^m + \overline{X}_t^f(\hat{\beta}_t^m - \hat{\beta}_t^f) + (\hat{\epsilon}_t^m - \hat{\epsilon}_t^f) \\ &= \Delta\overline{X}_t \hat{\beta}_t^m + \overline{X}_t^f \Delta\hat{\beta}_t + \Delta\hat{\epsilon}_t\end{aligned}$$

By this way the gender wage gap at time t defined in Equation 11 is decomposed into three components: (i) a portion due to gender differences in characteristics and skills ($\hat{\beta}_t^m \Delta\overline{X}_t$), (ii) a portion due to gender differences in returns to characteristics and skill prices ($\overline{X}_t^f \Delta\hat{\beta}_t$), and (iii) a proportion due to residual gap ($\Delta\hat{\epsilon}_t$). Similarly, given the gender wage gap at two different time periods time t and time s, the change in average gender wage gap over time can be decomposed as:

$$\begin{aligned}\Delta\overline{lnW_s} - \Delta\overline{lnW_t} &= [(\Delta\overline{X_s} - \Delta\overline{X_t})\hat{\beta}_t^m] \\ &+ [\Delta\overline{X_s}(\hat{\beta}_s^m - \hat{\beta}_t^m)] + \\ &+ [\Delta\hat{\epsilon}_s - \Delta\hat{\epsilon}_t]\end{aligned} \tag{13}$$

[25] We follow the parametrization by Blau and Kahn (1997) by formulating the wage gap based on male's wage equation. This approach lies in the assumption that the prices from the male regression are equivalent to competitive prices. Since, male-female differences in returns can reflect discrimination, the use of male's equation let us to simulate the wage equation in a nondiscriminatory labor market.

where in this case the change in gender wage gap between time t and time s is decomposed into three components as i)a portion due to the changes in gender differences in characteristics and skills $((\Delta\overline{X_s} - \Delta\overline{X_t})\hat{\beta}_t^m)$, (ii) a portion due to the changes in gender differences in returns to characteristics and skill prices $(\Delta\overline{X_s}(\hat{\beta}_s^m - \hat{\beta}_t^m))$, and (iii) a proportion due to the changes in residual gap $(\Delta\hat{\epsilon}_s - \Delta\hat{\epsilon}_t)$. Juhn, Murphy and Pierce (1991) provides a further decomposition of the third component using the standardized residuals ϕ and the residual standard deviations of wages, σ such that:

$$
\begin{aligned}
\Delta\overline{lnW_s} - \Delta\overline{lnW_t} &= [(\Delta\overline{X_s} - \Delta\overline{X_t})\hat{\beta}_t^m] \\
&+ [\Delta\overline{X_s}(\hat{\beta}_s^m - \hat{\beta}_t^m)] + \\
&+ (\Delta\overline{\phi_s} - \Delta\overline{\phi_t})\hat{\sigma}_t^m \\
&+ \Delta\overline{\phi_s}(\hat{\sigma}_s^m - \hat{\sigma}_t^m)
\end{aligned} \tag{14}
$$

In this four component decomposition, the first two components: (i) the average effect of change in gender differences in observed human capital and skills $[(\Delta\overline{X_s} - \Delta\overline{X_t})\hat{\beta}_t^m]$ and (ii) the average effect of changing prices $[\Delta\overline{X_s}(\hat{\beta}_s^m - \hat{\beta}_t^m)]$ constitute the part of difference in the gender pay gap due to the difference in predicted gap (i+ii). Difference in residual gap is the sum of third and the forth components (iii+iv): (iii) the average effect of changes in the levels of the unobservables, in other words, changes of female standardized residuals in males residual distribution $(\Delta\overline{\phi_s} - \Delta\overline{\phi_t})\hat{\sigma}_t^m$ and (iv) average unobserved price effect, i.e. change in the dispersion of male residual distribution $\Delta\overline{\phi_s}(\hat{\sigma}_s^m - \hat{\sigma}_t^m)$. On the other hand, the sum of first and third component are interpreted as the average composition effect (i+iii) on gender wage gap changes, while the sum of the second and the forth as the labor market or wage structure effect (ii+iv).

7.2 Decomposition Results

This subsection presents the results from the decomposition of changes in the gender wage gap in Austria, Ireland, Italy. Portugal, Spain and the UK. For this purpose, first, the empirical model specified in Equation 2 is estimated for males and females separately (in this case without including the female dummy). Second, the change in gender wage gap between 1995 and 2009 decomposed into its components for each country using the JMP technique. Hence, the change in the gender wage gap in each country attributed to four components; (i) changes in the observable worker characteristics and skills; (ii) the observable changes in returns to these characteristics and skills; (iii) changes in unobservable quantities and (iv) changes in unobservable prices, is quantified. Then, to isolate the effect of skills from the other human capital variables that we controlled for (education and experience) we split the first two components (i and ii) and quantify the role of changing skills and skill prices on gender wage gap trends. The decomposition results for each country are presented in Table 2. Panel A of Table 2 presents the initial decomposition results where change in gender wage gap between 1995 and 2009 broken down into its four components, while Panel B focus on the effect of change in skills and skill prices.

The first columns (I) of two panels are identical and present the average change in the gap between 1995 to 2009 in each country. Note that, the change in the gender wage gap between 1995 and 2009 is equal to the difference between the coefficient estimates for the corresponding years presented in Figure 1 and Table E.1 in Appendix E. The difference presented in Table 2 has been transformed in a way that a negative coefficient implies a decline in the gap. As discussed in Section 4, the first column of Table 2 shows the decline in the gap from 1995 to 2009 in all countries. The columns of Panel A from second to the fifth (II-V) present the contribution of each component to the narrowing gender wage gap and the sum of these four columns (II-V) gives the overall change in raw gap (Column I). A negative coefficient implies a decreasing effect of the corresponding component on the gender wage gap, while a positive coefficient shows a widening effect. According to the results presented in Panel A, in all countries, the decline in the average gender wage gap driven by the changes in observed (II) and unobserved quantities (IV) in common. As mentioned before, the sum of these two components (II+IV) are interpreted as average effect of the changes in worker composition. Given the trends in labor market outcomes described in Section 2.1, we can conclude that the narrowing gender wage gap in the European labor markets between 1995-2009 occurred mostly due to the improved observed and unobserved characteristics and skills of women. On the other hand, overall effect of the changes in observable and unobservable prices on the gender wage gap is the effect of changes in the wage structure. As shown in Panel A, the coefficients for these two components (Columns III and V) are either positive or relatively negligible implying a widening effect of changes on the wage structures. This implies the following: The gender wage gap narrowed in all European countries. The gap would narrow even further in the absence of changes in the wage structure in countries where these components are positive. In countries, where these components are negative (for example in Austria), the major factor in explaining the narrowing the gap is still the effect of worker composition. The effect of each component in gender wage gap trends in European labor markets is similar to the patterns in the US labor market explored by earlier studies. Blau and Kahn (1997) and Bacolod and Blum (2010) show that, in the US labor market, the wage structure effect is small or leads to a widening gender wage gap, while the composition effect mostly explains the narrowing gender wage gap. Our results suggest that the effect of changes in worker composition is also the driving force of the narrowing gender wage gap in European labor markets.

What is the role of skills in explaining the narrowing gender wage gap? Panel B of Table 2 addresses this question. As before, column I of Panel B presents the average change in the gender wage gap between 1995-2009. The second column is the total effect of skills, including the changes in skill intensities and changes in returns to skills. In this case, European countries are clustered in two groups: (i) countries where the skills widened the gap (Italy, Portugal and Spain, and the UK) and (ii) countries where the skills contribute to the narrowing gender wage gap (Austria and Ireland). The third and the forth column of Panel B separates the price and quantity effects of skill changes and the sum of these two columns adds up to the coefficient presented in column II of Panel B. A common feature for all the countries is the widening effect of changes in skill prices, except in Austria. On the other hand, except in Spain and the UK, the change in the brain and brawn intensity of males and females explains a part of the narrowing gender wage gap.

Our decomposition results reveal the heterogeneity across European countries. Simultaneous changes in skill intensity of jobs held by men and women and change in returns

Table 2: Decomposition of the changes in gender wage gap, 1995 vs 2009

Panel A	ΔGender Wage Gap (I)	ΔObserved Quantities (II)	ΔObserved Prices (III)	ΔUnobserved Quantities (IV)	ΔUnobserved Prices (V)
Austria	-0.068	-0.010	-0.005	-0.050	-0.003
Ireland	-0.156	-0.065	0.024	-0.101	-0.014
Italy	-0.030	-0.053	0.049	-0.035	0.008
Portugal	-0.033	-0.075	0.047	-0.012	0.007
Spain	-0.019	0.003	0.042	-0.030	-0.034
UK	-0.052	0.038	0.032	-0.128	0.006
Panel B	ΔGender Wage Gap (I)	Part Explained by Brains and Brawns (II)	Contribution of ΔBrains and ΔBrawns (III)	Contribution of ΔPrices of Brains and Brawns (IV)	
Austria	-0.068	-0.022	-0.012	-0.010	
Ireland	-0.156	-0.002	-0.016	0.014	
Italy	-0.030	0.013	-0.016	0.029	
Portugal	-0.033	0.007	-0.013	0.020	
Spain	-0.019	0.026	0.008	0.018	
UK	-0.052	0.063	0.017	0.046	

to brain and brawn skills made different effects in different countries. In Mediterranean countries (Italy, Portugal and Spain) and in the UK the gender wage gap narrowed between 1995 and 2009, despite the opposite effect of skills. In contrary, the changes in skills and returns to skills explain a part of the narrowing gender wage gap in Austria and Ireland. However, it is striking that, the gender wage gap narrowed in the European labor markets except in Austria, despite the widening effect of changes returns to "brains" and "brawns". This result contradicts with the earlier findings by Bacolod and Blum (2010) which provide suggestive evidence for the role of changing skill prices in narrowing the gender wage gap in the US. On the other hand, some of our results are consistent with the findings of Black and Spitz-Oener (2006 and 2010) for West Germany. Similar to our findings for European countries except Austria, Black and Spitz-Oener (2006 and 2010) provide evidence on the changes in task prices contributed to widening the gender gap in West Germany between 1979 and 1999. They find that changes in the relative task and relative price changes together explain more than 40 percent of the narrowing of the gender gap in West Germany. While further analysis is required to understand in detail the reasons for the difference across these countries and the US, our analyses suggest that in the European labor markets, the returns to "brains" versus "brawns" did not change in favor of "brains". Hence, the narrowing gender wage gap occured despite the widening effect of changes in skills in the European labor markets.

8 Concluding Remarks

This paper explores the role of changes in skill intensity of males and females and the changes in skill prices on the gender wage gap trends in the European labor markets. For understanding the role of skills, we focus on two broadly defined skills required by the occupations: "brains" and "brawns" diverging from the traditional measures of worker skills.

Our results suggest that between 1995 and 2009, the gender wage gap narrowed in Austria, Ireland, Italy, Portugal, Spain and in the UK. The change in the worker composition, in particular improved observable and unobservable characteristics of female workers was the major factor explaining the narrowing gap in European labor markets.

Following the earlier empirical results, in particular for the US, our initial hypothesis was the changing labor demand favors occupations that are more intensive in "brain" skills where women are over-represented. Indeed, we find that women are over-represented in such occupations and they are increasingly represented in those occupations. We show that women experienced larger relative increases in brain skills and declines in brawn skills than men from 1995 to 2009 in the European countries. Our decomposition analysis reveal that, in countries where the changes in skill intensities were larger for females, in Austria, Ireland, Italy and in Portugal, skill changes are able to account for a substantial fraction of the closing of the gender wage gap during this period. On the other hand, in countries where males experienced relatively larger changes in the work content by increasing their representation in brain intensive occupations, like in Spain and in the UK, changes in skill intensities had a widening effect.

In addition, our results suggest that the gender wage gap narrowed despite the widening effect of changes in wage structure. In other words, in the absence of any price changes, the gender wage gap would narrow even further from 1995 to 2009. Considering our initial hypothesis, we further investigate whether the changes in skill prices account for the narrowing gender wage gap in the European labor markets as it did for the US labor market in 1980s. We find that, returns to "brains" versus "brawns" did not change in favor of "brains", on the contrary.

This result is striking in comparison to the results of the earlier studies for the US. There are potential explanations for this difference across European countries and the US. Indeed, earlier studies provide evidence on the relatively small changes in relative demand for skills and wage inequality in Europe between the 1970s and 1990s (Acemoglu, 2002). Some studies attribute these differences to the faster increase in relative supply of skills in Europe or to the role of European labor market institutions (Acemoglu, 2002; Greiner et al., 2004). The existing literature show that the US labor market is more dynamic and flexibility than the European labor markets (Nickell, 1997). Some studies argue this to be the main reason for the diverging effects of the same skill-biased technological change in the US and in Europe. For instance, Blau and Kahn (2002) suggest that in the flexible labor markets as in the US, low-skill workers work for lower wages to reflect their lower productivity while in many European countries due to labor market institutions which prevent a wage adjustment, employers reduce their employment of low-skill workers. Considering the declining unemployment rates and relative wages in the US, and the rising unemployment and comparatively stable relative wage levels in the many European countries may support this argument. However, to understand the reasons for these differences in detail, further analysis of the US and the European labor markets in a comparative perspective is required.

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Appendices

Appendix A. Selected Labor Market Statistics

Source: World Development Indicators, The World Bank , 2012.

Figure A.1: Labor force participation rates, % of population ages 15+: 1980-2009

Table A.1: Proportion of males and females with tertiary education, by age group, 2008

	Age Group			
	25-34		45-54	
	Males	Females	Males	Females
Austria	18.6	20.2	21.4	14.0
Ireland	37.9	52.2	26.4	27.7
Italy	15.5	24.4	12.0	11.8
Portugal	16.8	29.7	8.7	11.0
Spain	34.2	43.7	25.4	22.2
United Kingdom	36.7	40.2	29.5	30.4
OECD average	32.0	40.2	26.3	26.3

Source: OECD (2010b), Education at a Glance

Table A.2: Selected labor market statistics for 25-54 year-olds

	Employment Rates 2009		Share of Part-time Employment 2009		Share of Temporary Employment 2009		Proportion of Female Managers 2007
	Males	Females	Males	Females	Males	Females	
Austria	88.5	79.5	4.2	33.0	4.0	5.1	26.8
Ireland	78.0	67.1	7.7	34.8	5.2	7.1	30.7
Italy	84.7	59.1	4.5	30.2	8.7	13.3	33.5
Portugal	84.5	74.9	2.2	8.9	18.6	21.2	31.8
Spain	77.3	63.8	3.3	20.0	22.8	25.9	32.9
UK	85.4	74.4	5.5	35.1	3.8	4.9	34.4
OECD average	85.5	70.9	4.4	21.7	8.6	11.0	29.3

Source: OECD Labour Force Statistics, 2010.

Table A.3: Parental leave schemes in weeks, child-care availability and wage setting mechanism

	Collective Bargaining Coverage(1)	Key Level of Collective Bargaining(2)	National Minimum Wage(3)	Childcare spending as % of GDP(4)	Pre-primary spending as a % of GDP(5)
Austria	98.0%	Industry	No	0.30	..
Ireland	44.0%	Firm	Yes	0.26	..
Italy	80.0%	Industry	No	0.15	0.47
Portugal	90.0%	Industry	Yes	0.00	0.36
Spain	60.3%	Industry	Yes	0.45	0.00
UK	33.0%	Firm	Yes	0.44	0.65

	FRE paid maternity leave/ Maternity eave (6)	FRE paid paternity leave/ Paternity leave(7)	FRE paid parental leave(8)	Parental leave (unpaid)(9)	Maximum length of leave for women(10)
Austria	16/16	0.4/0.4	19.3	84.7	112.0
Ireland	6.6/42	0/14	0.0	14.0	42.0
Italy	16/20	..	7.8	18.2	26.0
Portugal	17/17	2.8/2.9	0.0	13.0	17.0
Spain	16/16	2.1/2.1	0.0	144.0	162.0
UK	12.8/52	0.1/2	0.0	13.0	52.0

Notes: (1) (i) Source: The respective EIRO Industrial relations profile (2009). (ii) Collective bargaining coverage shows the percentage of employees covered by collective agreements.(2-3) Source:Broughton (2009). Wage formation in the EU. European Foundation for the Improvement of Living and Working Conditions. (4-5)(i) Source: OECD Family database PF3.1 www.oecd.org/social/family/database. ii) Public expenditure (on childcare and early education services per cent of GDP referes to the year 2007. (6-10) (i) Source:OECD Family database PF2.1 www.oecd.org/social/family/database. (ii) FRE:Full time equivalent payment.

Appendix B. Data Sources and Summary Statistics

European Community Household Panel (ECHP)

The European Community Household Panel (ECHP) is a standardized longitudinal survey coordinated and supported by Eurostat. The survey includes a representative panel of households and individuals in each country, covering a wide range of topics on income, employment, poverty and social exclusion, housing, health, migration, and other social indicators. The major aim of the survey was to provide comparable information on EU population representative both at longitudinal and at crosswise level. The target population of ECHP is composed by all the resident persons living in private houses inside the EU. The unit of analysis are the families and, within the households, all individuals older than 16. All surveys in the ECHP are based on probability (random) sampling by design and probability sampling weights are provided with the data.

The survey began in 1994 (wave 1) in twelve EU countries. Although the ECHP is a common household survey for Member States, the collection of data takes place under the control of National Data Collection Units in each country. New household panels were established in all countries, except in Belgium, the Netherlands, Germany, Luxembourg and United Kingdom who developed ECHP as a continuation of existing national panels. In 1995 (wave 2) Austria joined the survey and Finland in 1996 (wave 3). From wave 4 (1997) Sweden provided cross-sectional information derived from its national survey. After a total duration of eight years (1994-2001), Eurostat decided to stop ECHP project and to replace it in 2003 with a new instrument, EU-SILC (Statistics on Income and Living Conditions).

European Union Statistics on Income and Living Conditions (EU-SILC)

The European Union Statistics on Income and Living Conditions (EU-SILC) builds upon and replaces the European Community Household Panel. Although, the objectives, and also content and methodology overlap with ECHP, there are major differences between two surveys. First, EU-SILC is rather a common framework defined on harmonized list of target primary (annual) and secondary (every four years or less frequently) variables. Second, EU-SILC main focus is on income, poverty, social exclusion and other living conditions, and detailed data are collected on income components, mostly on personal income, although a few household income components are included. Third, EU-SILC is a four-year rotated panel instead of a full panel. It provides two types of annual data: cross-sectional data and longitudinal data observed periodically over a four-year period.

EU-SILC was launched in 2003 in six Member States (Austria, Belgium, Denmark, Greece, Ireland, Luxembourg) and Norway. It was formally launched in 2004 in fifteen countries and expanded in 2005 to cover all of the EU-25 Member States, together with Norway and Iceland. Bulgaria introduced the survey in 2006, Romania, Switzerland and Turkey in 2007.

The reference population in EU-SILC includes all private households and all household members aged 16 and more are surveyed. The cross-sectional and longitudinal (initial sample) data are nationally representative of the target population within each country. Probability sample weights are provided with the data to generate descriptive information about the population.

Occupational Information Network (O*Net)

The Occupational Information Network (O*NET) program is developed under the sponsorship of the US Department of Labor/Employment and Training Administration. O*NET provide a continually updated database, which is available to the public at no cost. Together with the database, the data dictionary and technical documentation are provided. The O*Net database and a web-base application including the information contained in the database provide occupational information for use by job seekers, workforce development offices, human resources professionals, students, researchers, and others. The 15th edition of O*Net database, which has been used in this study contains several variables that represent descriptors of work and worker characteristics, including skill requirements. Information is collected using a two-stage design in which first businesses expected to employ workers in the targeted occupations are identified and second the sample of workers in those occupations within those businesses are selected. To reduce the burden on respondents the questions have been organized into four questionnaires, each containing a different set of questions. The sampled job incumbents for each occupation are randomly assigned one of the four questionnaires. All respondents are asked to complete the questionnaire together with the task questionnaire and provide some general demographic information together with one of the four questionnaires. The ability questionnaire, which has been used in this paper is completed by occupational analysts using the updated information from incumbent workers.

Table B.1: Summary statistics on female and male workers, 1995 and 2009

	Austria				Ireland				Italy			
	1995		2009		1995		2009		1995		2009	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Log(hourly wage)	2.18	2.43	2.32	2.53	2.06	2.25	2.58	2.68	2.08	2.15	2.17	2.23
Primary edu(%)	0.21	0.14	0.12	0.08	0.22	0.36	0.15	0.25	0.38	0.51	0.25	0.39
Secondary edu (%)	0.69	0.78	0.52	0.59	0.53	0.41	0.25	0.23	0.49	0.39	0.46	0.44
High edu (%)	0.10	0.08	0.35	0.33	0.25	0.22	0.58	0.48	0.13	0.10	0.28	0.17
Experience (year)	15.29	16.76	19.49	22.17	14.77	17.47	18.34	22.03	14.19	17.34	16.45	18.61
Permanent cont. (%)	0.89	0.90	0.93	0.95	0.78	0.88	0.92	0.94	0.88	0.91	0.84	0.87
Ful-time (%)	0.77	0.98	0.60	0.96	0.76	0.95	0.68	0.90	0.78	0.96	0.78	0.96
Married (%)	0.56	0.64	0.50	0.56	0.56	0.63	0.55	0.63	0.68	0.74	0.58	0.61
Number of obs.	1180	1767	2014	2398	1071	1556	1449	1508	1775	2893	6090	7498
	Portugal				Spain				UK			
	1995		2009		1995		2009		1995		2009	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Log(hourly wage)	1.24	1.35	1.59	1.68	1.99	2.11	2.20	2.31	2.09	2.36	2.48	2.69
Primary edu(%)	0.75	0.85	0.57	0.71	0.42	0.58	0.29	0.41	0.45	0.38	0.02	0.01
Secondary edu (%)	0.14	0.10	0.19	0.16	0.22	0.18	0.24	0.22	0.25	0.25	0.51	0.48
High edu (%)	0.10	0.05	0.22	0.10	0.36	0.23	0.47	0.36	0.30	0.37	0.48	0.51
Experience (year)	16.46	19.15	19.48	22.58	13.89	18.46	16.49	20.89	18.63	18.35	15.76	19.21
Permanent cont. (%)	0.81	0.83	0.79	0.82	0.61	0.66	0.77	0.81	0.90	0.92	0.98	0.96
Ful-time (%)	0.92	0.99	0.95	0.99	0.85	0.97	0.83	0.97	0.70	0.97	0.68	0.95
Married (%)	0.67	0.67	0.64	0.65	0.56	0.71	0.54	0.63	0.63	0.66	0.55	0.64
Number of obs.	1507	2189	1675	1832	1410	2864	4447	5194	3318	3487	540	542

Data Source: European Community Household Panel (ECHP, 1995-2001) and European European Union Statistics on Income and Living Conditions (EU-SILC, 2004-2009). *Notes:* Sample includes working age [16-64] population, working 15+ hours per week, with valid observations on all the variables used in the wage equations. The hourly wage is derived by multiplying gross monthly wage by (12/52)/(hours worked per week). Hourly wages are converted into 2001 PPP units using the purchasing power parity (PPP) exchange rates and defl?ated by using the harmonized consumer price index (HCPI, base 2001). Wage observations ten times greater than the 99th percentile and ten times lower than the 1th percentile of the wage distribution in the each country are excluded.

Table B.2: Female share and concentration in occupations, 1995

	Austria		Ireland		Italy		Portugal		Spain		UK	
	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F
Legislators, senior officials and corporate managers	13	1.4	16	0.9	15	0.9	18	0.5	12	0.7	31	6.3
Managers of small enterprises	21	0.9	23	2.0	6	0.1	24	0.3	26	0.7	37	2.3
Physical, mathematical, engineering, life science and health professionals	45	2.9	57	9.7	31	1.8	27	1.1	37	5.0	33	4.5
Teaching professionals	55	2.5	60	10.8	68	10.3	72	4.5	61	11.6	64	7.2
Other professionals	45	0.8	32	2.2	38	0.9	47	1.1	43	2.8	57	4.4
Physical, engineering, life science and health associate professionals	30	5.8	34	3.3	50	6.1	39	3.2	28	2.8	58	6.5
Teaching and other associate professionals	47	13.1	42	6.8	45	9.1	56	7.9	39	8.4	45	5.2
Office and customer services clerks	68	27.9	66	24.5	48	32.6	57	17.1	52	18.8	73	28.8
Personal and protective services workers	56	12.3	55	12.3	45	5.1	63	18.4	47	13.4	70	13.2
Models, salespersons and demonstrators	78	10.7	69	9.3	45	3.4	45	5.6	50	8.3	76	7.0
Skilled agricultural and fishery workers	21	0.8	0	0.0	19	0.8	25	2.3	7	0.4	14	0.2
Extraction, building, other craft and related trades workers	14	3.6	6	0.9	26	7.3	28	11.8	13	4.5	18	1.2
Metal, machinery, precision, handicraft, printing and related trades workers	7	1.4	8	1.1	17	4.9	8	1.6	4	1.0	6	0.8
Stationary-plant and related operators, drivers and mobile-plant operators	6	0.9	2	0.3	10	1.3	4	0.6	1	0.2	6	0.5
Machine operators and assemblers	30	1.4	47	8.5	22	1.0	49	4.6	26	2.4	42	4.3
Sales and services elementary occupations	70	10.0	61	4.6	48	9.1	71	15.4	59	15.3	67	5.6
Agricultural, fishery and related laborers	50	0.5	6	0.3	43	2.7	35	2.5	26	1.6	27	0.3
Laborers in mining, construction,manufacturing and transport	25	3.0	18	2.5	27	2.8	15	1.7	12	2.2	36	1.8
Dissimilarity Index	45.93		43.17		28.56		39.75		42.06		40.86	

Note: F_i/T_i = female employees in occupation i as percentage of total employees in occupation i. F_i/F = female employees in occupation i as a percentage of female employees. The dissimilarity index (ID) is calculated as follows: $ID = [1/2 \sum[F_i/F - M_i/M]] * 100$. The ID has a minimum value 0 when there is same percentage of female and male in each occupation and a maximum value of 100 when each occupation is completely male or female.

Table B.3: Female share and concentration in occupations, 2009

	Austria		Ireland		Italy		Portugal		Spain		UK	
	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F
Legislators, senior officials and corporate managers	25	2.1	38	11.1	32	1.1	27	1.4	25	0.8	34	10.4
Managers of small enterprises	29	0.8	51	3.0	36	0.7			29	0.3	35	1.1
Physical, mathematical, engineering, life science and health professionals	34	2.2	51	8.2	38	2.9	53	4.2	50	7.7	20	3.0
Teaching professionals	60	6.5	66	8.5	63	5.5	71	5.1	64	9.2	66	9.4
Other professionals	56	3.6	54	7.7	52	3.2	63	4.1	54	3.9	43	3.5
Physical, engineering, life science and health associate professionals	23	4.4	35	2.4	40	8.0	25	1.9	42	3.9	62	8.7
Teaching and other associate professionals	56	15.1	50	4.4	66	21.4	66	9.0	48	7.6	64	8.7
Office and customer services clerks	71	27.3	75	21.5	58	19.9	65	15.9	66	22.7	81	23.9
Personal and protective services workers	66	13.3	63	14.6	55	9.5	68	17.9	60	13.2	83	18.7
Models, salespersons and demonstrators	76	9.6	75	8.5	67	6.7	72	7.4	68	8.9	55	4.8
Skilled agricultural and fishery workers	44	0.6	18	0.1	22	0.6	19	0.9	16	0.4	0	0.0
Extraction, building, other craft and related trades workers	6	0.9	6	0.5	18	3.7	24	6.9	12	2.3	14	0.7
Metal, machinery, precision, handicraft, printing and related trades workers	4	0.4	7	0.6	11	1.4	4	0.5	5	0.5	0	0.0
Stationary-plant and related operators, drivers and mobile-plant operators	3	0.3	6	0.4	7	1.0	4	0.6	4	0.5	9	0.6
Machine operators and assemblers	27	0.9	50	1.4	35	3.5	44	3.5	27	1.6	19	0.7
Sales and services elementary occupations	69	8.9	52	3.4	63	9.2	74	19.4	70	13.7	53	4.8
Agricultural, fishery and related laborers	17	0.1	30	0.2	46	1.3	45	0.3	35	0.7	0	0.0
Laborers in mining, construction,manufacturing and transport	26	2.8	27	3.5	11	0.5	21	1.1	20	2.0	14	0.9
Dissimilarity Index	47.25		33.88		36.16		46.90		39.97		46.79	

Note: F_i/T_i = female employees in occupation i as percentage of total employees in occupation i. F_i/F = female employees in occupation i as a percentage of female employees. The dissimilarity index (ID) is calculated as follows: $ID = [1/2\sum[F_i/F - M_i/M]] * 100$. The ID has a minimum value 0 when there is same percentage of female and male in each occupation and a maximum value of 100 when each occupation is completely male or female. For Portugal EU-SILC does not differentiate two occupational categories: 1112-Legislators, senior officials and corporate managers and 1300-Managers of small enterprises.

Appendix C. Occupational Skill Requirements

Table C.1: Descriptors comprising the skill measures

Variables comprising BRAIN SKILLS measure

O*Net Descriptor	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.

Variables comprising BRAWN SKILL measure

O*Net Descriptor	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.

Mapping of O*Net-SOC Occupational Codes to ISCO Codes

15th edition of O*Net occupational coding is based on SOC 2010, but there exist differences between two occupation codes. O*Net splits up several SOC 2010 occupations into multiple separate occupations. O*Net includes 1110 occupations with detailed information in the database for 974 of them, while SOC 2010 includes 840 detailed occupations. 667 occupations in 15th edition of O*Net are at SOC level which we have the ability requirements and employment shares of these occupations in the 2001 US labor market. 37 SOC level occupations are with detailed O*Net level. For instance, SOC 2010 code 11-3031 is Financial Managers, which O*Net provides information on ability requirements, but divides up this category into further two categories 11-3031.01, Treasurers and Controllers; and 11-3031.02 Financial Managers, Branch or Department which we have their ability requirements separately but do not have their employment shares separately. We have dealt with these O*NET categories by simply taking the descriptor values for the main 37 occupation titles (for this example the values for 11-3031, Financial Managers are taken into account). 269 occupations in 15th edition are detailed O*Net occupations which do not exist in SOC 2010 separately. For instance, SOC code 13-2011 is Accountants and Auditors, which O*NET divides up into 13-2011.01, accountants; and 13-2011.02, auditors and provides the ability requirements of detailed categories (for 13-2011.01 and 13-2011.02) but not for the main category (13-2011). Since we do not have the employment shares of the detailed categories we deal with these categories by taking a simple mean of the descriptor values to determine the skill requirement of main title (for this example we took the simple average of descriptor values for occupations 13-2011.01 and 13-2011.02 to determine the skill requirement of 13-2011, Accountants and Auditors). There is 1 exceptional case in O*Net classification 19-1020.01 Biologists which does not exist in SOC classification, which we excluded from the analysis. Information on abilities is collected for 854 occupations among those 1100.

After determining the descriptor values of all SOC 2010 level occupations we proceed as follow: First, using the ISCO-SOC 2000 made available by the Center for Longitudinal Studies in the UK at http://www.cls.ioe.ac.uk/text.asp?section=000100010005001600002, we matched ISCO codes with SOC 2000 codes. Then using SOC 2000-SOC 2010 crosswalk provided by Integrated Public Use Microdata Series (IPUMS-USA) we matched the ISCO codes with SOC 2010 codes. Finally O*Net codes are matched with ISCO codes using these two crosswalks. Finally, using the employment shares of SOC 2010 codded occupations for 2001 are derived from Occupational Employment Statistics Survey 2010 by Bureau of Labor Statistics, descriptor values of broader occupational titles are determined. In total 849 O*Net occupations are classified under broad categories of ISCO level occupations with total employment share 97% in 2001 in the US labor market.

For Portugal EU-SILC does not differentiate two occupational categories: 1112, Legislators, senior officials and corporate managers and 1300, Managers of small enterprises. Only for Portugal, these two occupations are aggregated while determining the descriptor values of broad level occupations.

Appendix D. Principal Component Analysis (PCA)

PCA Technique

Principle Component Analysis is a variable reduction technique which maximizes the amount of variance accounted for in the observed variables by a smaller group of variables called components. The components are not latent factors. PCA is not a model based technique and involves no hypothesis about the substantive meaning of or relationships between latent factors. Technically, let the random vector $\mathbf{X}' = [X_1, X_2, ..., X_p]$ be our observable measures with the covariance matrix $\sum$ with eigenvalues $\lambda_1 \geqslant \lambda_2 \geqslant ...\lambda_p \geqslant 0$. The linear combinations:

$$\begin{aligned}
Y_1 &= \mathbf{a}_1'\mathbf{X} = \mathbf{a}_{11}X_1 + a_{12}X_2 + ... + a_{1p}X_p \\
Y_2 &= \mathbf{a}_2'\mathbf{X} = \mathbf{a}_{21}X_1 + a_{22}X_2 + ... + a_{2p}X_p \\
&\quad ... \\
Y_p &= \mathbf{a}_p'\mathbf{X} = \mathbf{a}_{p1}X_1 + a_{p2}X_2 + ... + a_{pp}X_p
\end{aligned}$$

with $Var(Y_i) = \mathbf{a}_i' \sum \mathbf{a}_i$ and $Cov(Y_i, Y_k) = \mathbf{a}_i' \sum \mathbf{a}_k, i, k = 1, 2, ..., p$ are the principle components i.e. components are uncorrelated linear combinations $Y_1, Y_2, ..., Y_p$ whose variances are as large as possible.Principle components are then defined by:

$$\begin{aligned}
\text{First principle component} &= \text{linear combination } \mathbf{a}_1'\mathbf{X} \\
\text{that maximizes } Var(\mathbf{a}_1'\mathbf{X}) \text{ st. } \mathbf{a}_1'\mathbf{a}_1 = 1 & \\
\text{Second principle component} &= \text{linear combination } \mathbf{a}_2'\mathbf{X} \\
\text{that maximizes } Var(\mathbf{a}_2'\mathbf{X}) \text{ st. } \mathbf{a}_2'\mathbf{a}_2 = 1 & \quad \text{and } Cov(\mathbf{a}_1'\mathbf{X}, \mathbf{a}_2'\mathbf{X}) = \mathbf{0} \\
& \quad ... \\
i^{th} \text{ principle component} &= \text{linear combination } \mathbf{a}_i'\mathbf{X} \\
\text{that maximizes } Var(\mathbf{a}_i'\mathbf{X}) \text{ st. } \mathbf{a}_i'\mathbf{a}_i = 1 & \quad \text{and } Cov(\mathbf{a}_i'\mathbf{X}, \mathbf{a}_k'X) = 0 \\
\text{for } k \neq i &
\end{aligned}$$

PCA can be also performed based on the correlation matrix. If the correlation matrix is used, the variables are standardized and the total variance will equal the number of variables used in the analysis since each standardized variable has a variance equal to one. The use of correlation-matrix is necessary when the variables have different scales of measurement or not measured in a natural scale. Principal components analysis is based on the correlation matrix of the variables involved need a large sample size to avoid computational difficulties. In this case, the total variance will be equal the number of variables used in the analysis because each standardized variable has a variance equal to one. As a rule of thumb, the number of principle are decided in order to have a cumulative variance explained by the components 50% - 70%. Kaiser criterion also suggests not to keep components with an eigenvalue of less than 1, since these components account for less variance than did the original variable. Scree plots represents the ability of principle components to explain the variation in data by showing the eigenvalues, or in other words the variance explained by each component. Moreover, component loadings of each variable involved in the analysis help to interpret the constructed component since they show the weight of each variable in forming the component score.

Constructing Skill Requirement of Occupations by PCA

As a robustness check we used Principle Component Analysis (PCA) to construct alternative measures of brain and brawn skills. PCA based on the correlation matrix has been widely used in the early research to construct task or skill measures from the various descriptors of DOT or O*Net data (Autor, Levy and Murnane, 2003; Bacolod and Blum, 2010; Goos, Manning and Salomons, 2009;Ortega and Polavieja, 2012). A common approach is performing Principal Component Analysis within the set of selected descriptors each of which is standardized with mean zero and variance one, subject to the constraint that the sum of squared weights in the eigenvector equals one and using the first principle components from each analysis to construct the skill measures (Autor, Levy and Murnane, 2003; Bacolod and Blum, 2010; Goos, Manning and Salomons, 2009). The main reason for constructing components from separate PCA instead of joint PCA is, that in the case of joint PCA components are orthogonal to each other by construction. Building skill measures using a principle component analysis of the all O*Net descriptors will be ruling out this possibility a priori.

Following the earlier literature that use PCA, we also construct alternative skill measures via PCA. For this purpose, we proceed as follow. First, we performed two separate PCAs using the O*Net ability descriptors of O*Net occupations (using the 849 O*Net occupations, those are matched with ISCO level occupations as explained in Appendix C). One performed among the cognitive ability descriptors and the other among psycho-motor ability descriptors together with physical ability descriptors. The first component of the first PCA explains around 50% of the variation among the cognitive ability descriptors, while most of the variation among the psycho-motor and physical ability descriptors are explained by first principal component (around 72% of the variation). Figure D.1 visually presents the ability of first principle components of each analysis to explain the variation in corresponding descriptor values. PCs based on transformation of correlation matrix to eigen-basis coordinates are unit free. If the loadings of all descriptors related to the same skill in the corresponding component is positive, then a higher component score implies a higher intensity in that skill. Table D.2 presents the component loadings of each descriptor involved in the analysis. All the cognitive ability descriptors have positive weights on the first principle component of the former PCA analysis (with one exception: Spatial Orientation), while all psycho-motor and physical ability descriptors have positive loadings on the first component of the later PCA without any exception. Hence we call the these components “brains” and “brawns” respectively.

Then again, to determine the brain and brawn skill requirement of broad classification of occupations we make use of the employment shares of SOC 2010 codded occupations for 2001 are derived from Occupational Employment Statistics Survey 2010 by Bureau of Labor Statistics. Basically, we took the weighted average of the component scores of occupations under the broad title where the weights are employment shares. And finally, we standardized the skill measures (mean 0, standard deviation 1). Table D.2 presents the summary statistics of brain and brawn skill measures constructed by this procedure.

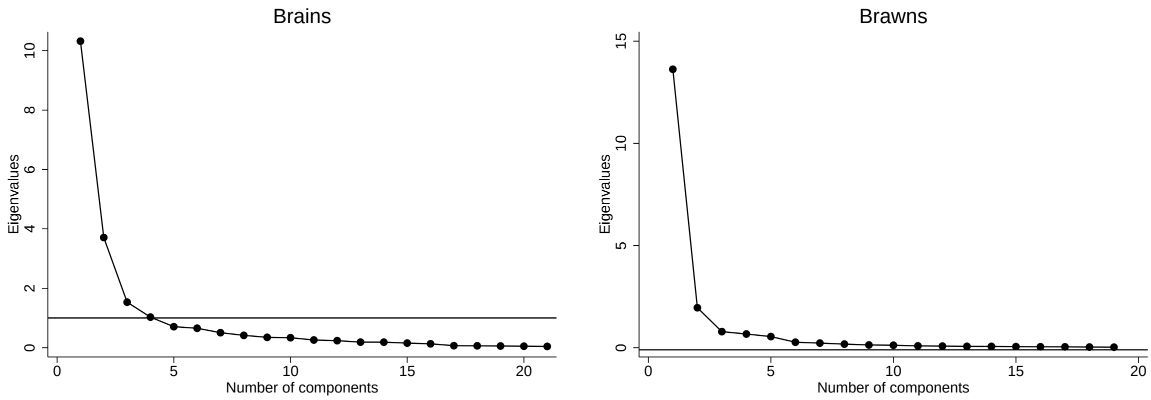

Figure D.1: Scree plot of eigenvalues after separate PCA

Table D.1: Principal component loadings

Brains		Brawns	
Descriptor	Component Loading	Descriptor	Component Loading
Oral Comprehension	0.219	Arm-Hand Steadiness	0.241
Written Comprehension	0.245	Manual Dexterity	0.241
Oral Expression	0.202	Finger Dexterity	0.177
Written Expression	0.240	Control Precision	0.233
Fluency of Ideas	0.258	Multilimb Coordination	0.258
Originality	0.243	Response Orientation	0.238
Problem Sensitivity	0.242	Rate Control	0.235
Deductive Reasoning	0.278	Reaction Time	0.241
Inductive Reasoning	0.270	Wrist-Finger Speed	0.214
Information Ordering	0.249	Speed of Limb Movement	0.241
Category Flexibility	0.251	Static Strength	0.257
Mathematical Reasoning	0.213	Explosive Strength	0.123
Number Facility	0.198	Dynamic Strength	0.250
Memorization	0.235	Trunk Strength	0.240
Speed of Closure	0.229	Stamina	0.246
Flexibility of Closure	0.216	Extent Flexibility	0.252
Perceptual Speed	0.143	Dynamic Flexibility	0.140
Spatial Orientation	-0.050	Gross Body Coordination	0.244
Visualization	0.092	Gross Body Equilibrium	0.234
Selective Attention	0.183		
Time Sharing	0.173		

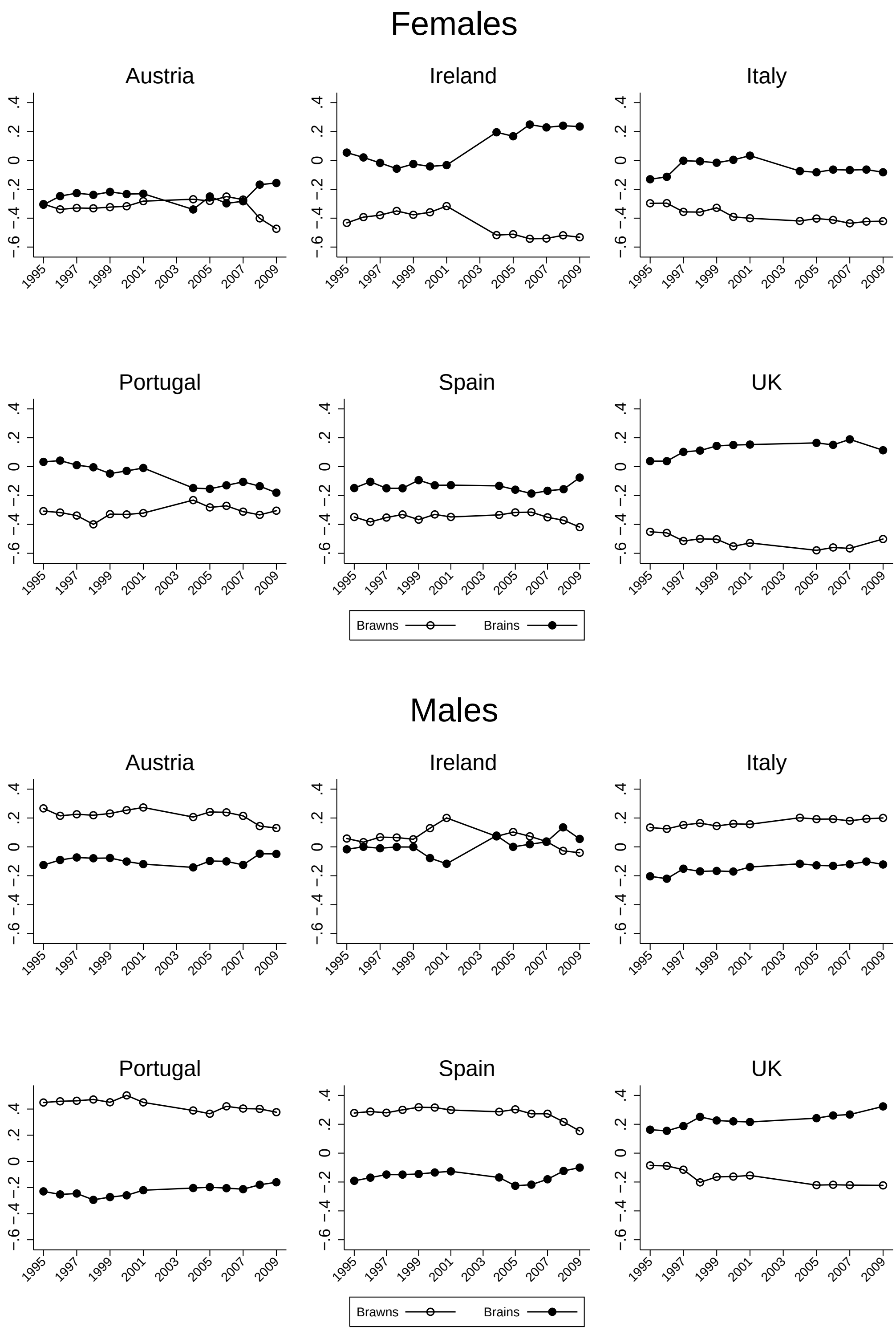

Figure D.2: Female and male intensity in brain and brawn skills constructed by PCA: 1995-2009

Table D.2: Brain and brawn skill intensity of occupations, using skill measures constructed by PCA

Occupation	Principle Component Values		Occupation
code	Brains	Brawns	title
1112	1.11	-1.05	Legislators, senior officials and corporate managers
1300	1.14	-1.27	Managers of small enterprises
2122	1.62	-0.57	Physical, mathematical, engineering, life science and health professionals
2300	1.29	-1.28	Teaching professionals
2400	1.06	-1.22	Other professionals
3132	0.64	0.08	Physical, engineering, life science and health associate professionals
3334	0.27	-1.35	Teaching and other associate professionals
4142	-0.19	-0.86	Office and customer services clerks
5100	-0.52	0.46	Personal and protective services workers
5200	-0.13	-0.44	Models, salespersons and demonstrators
6100	-1.04	1.10	Skilled agricultural and fishery workers
7174	-0.19	1.22	Extraction, building, other craft and related trades workers
7273	-0.22	0.99	Metal, machinery, precision, handicraft, printing and related trades workers
8183	-0.44	1.29	Stationary-plant and related operators, drivers and mobile-plant operators
8200	-0.81	0.61	Machine operators and assemblers
9100	-1.97	0.24	Sales and services elementary occupations
9200	-0.11	1.11	Agricultural, fishery and related laborers
9300	-1.52	0.93	Laborers in mining, construction,manufacturing and transport
Mean	0	0	
Std. dev.	1	1	
Pearson correlation coefficient	-0.68		

Note: Occupation codes are based on regrouped (group B) classification of ECHP data. If the occupations are regrouped, the first and the last two digits of the occupation code corresponds to the 2-digit ISCO-88 classification of occupations.

Appendix E. Wage Regression Results and Robustness Checks

Table E.1: Female dummy coefficient estimates, 1995-2009

	1995					
	Austria	Ireland	Italy	Portugal	Spain	UK
Female	-0.268***	-0.214***	-0.087***	-0.136***	-0.127***	-0.274***
	(0.025)	(0.028)	(0.014)	(0.029)	(0.021)	(0.013)
R-squared	0.065	0.032	0.012	0.012	0.011	0.071
Number of obs.	2947	2627	4668	3696	4274	6803
	2009					
	Austria	Ireland	Italy	Portugal	Spain	UK
Female	-0.200***	-0.058	-0.057***	-0.103***	-0.109***	-0.222***
	(0.016)	(0.030)	(0.009)	(0.023)	(0.012)	(0.036)
R-squared	0.043	0.003	0.005	0.009	0.013	0.042
Number of obs.	4412	2957	13588	3507	9641	1082

Notes: (i)Standard errors are in parentheses. (ii)*, ** and *** significant at 1,5 and 10 % significance level respectively. (iii)Raw gender gap includes gender dummy without any control variables.(iv)All models include the constant term.

Table E.2: Wage Regression Estimates

	Austria		Ireland		Italy		Portugal		Spain		UK	
	1995	2009	1995	2009	1995	2009	1995	2009	1995	2009	1995	2009
Female	-0.265***	-0.193***	-0.259***	-0.125**	-0.141***	-0.115***	-0.233***	-0.223** *	-0.209***	-0.138***	-0.256***	-0.155***
	(0.05)	(0.03)	(0.05)	(0.04)	(0.02)	(0.02)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Secondary education	0.110*	0.104***	0.218***	0.088	0.126***	0.105***	0.257***	0.224** *	0.193***	0.130***	0.116***	-0.000
	(0.04)	(0.02)	(0.03)	(0.06)	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)	(0.03)	(0.02)	(0.08)
Higher education	0.324***	0.315***	0.481***	0.325***	0.358***	0.277***	0.814***	0.695** *	0.430***	0.310***	0.299***	0.211*
	(0.06)	(0.04)	(0.08)	(0.05)	(0.04)	(0.03)	(0.13)	(0.09)	(0.05)	(0.04)	(0.04)	(0.09)
Experience	0.016***	0.023***	0.032***	0.031***	0.012***	0.029***	0.027***	0.037** *	0.026***	0.027***	0.026***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000*	-0.000***	-0.000***	-0.001** *	-0.000***	-0.000***	-0.001***	-0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Brains	0.583***	0.597***	0.668***	0.638***	0.337**	0.490***	0.617*	0.452**	0.627***	0.657***	0.671***	0.985***
	(0.09)	(0.05)	(0.15)	(0.16)	(0.10)	(0.10)	(0.22)	(0.13)	(0.14)	(0.12)	(0.12)	(0.14)
Brawns	-0.297***	-0.277***	-0.363*	-0.191	-0.405***	-0.263**	-0.730***	-0.479**	-0.453***	-0.294**	-0.276**	-0.152
	(0.06)	(0.04)	(0.13)	(0.11)	(0.05)	(0.07)	(0.12)	(0.13)	(0.07)	(0.08)	(0.09)	(0.09)
Constant	2.014***	1.844***	1.584***	1.820***	1.990***	1.703***	1.223***	1.221** *	1.669***	1.655***	1.752***	1.941***
	(0.09)	(0.07)	(0.13)	(0.13)	(0.05)	(0.10)	(0.13)	(0.12)	(0.11)	(0.13)	(0.08)	(0.13)
Mean VIF	4.74	5.70	4.50	4.64	4.33	5.03	4.28	4.75	4.39	4.70	4.97	8.29
R-squared	0.231	0.346	0.402	0.336	0.366	0.334	0.569	0.511	0.435	0.449	0.379	0.345
Number of obs.	2947	4412	2627	2957	4668	13588	3696	3507	4274	9641	6803	1082

Notes: i) 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$= 1 - (1 - R_i{}^2)$ where $R_i{}^2$ is the coefficient of determination of the regression equation where each explanatory variable regressed on all the other explanatory variables.

Table E.3: Robustness Check: Wage Regression Estimates, Expanded Model

	Austria		Ireland		Italy		Portugal		Spain		UK	
	1995	2009	1995	2009	1995	2009	1995	2009	1995	2009	1995	2009
Female	-0.276***	-0.182***	-0.241***	-0.087*	-0.160***	-0.110***	-0.240***	-0.222***	-0.189***	-0.126***	-0.210***	-0.128**
	(0.05)	(0.02)	(0.04)	(0.04)	(0.01)	(0.02)	(0.05)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)
Secondary education	0.096	0.102***	0.211***	0.084	0.124***	0.102***	0.259***	0.226***	0.149***	0.123***	0.118***	0.023
	(0.05)	(0.02)	(0.03)	(0.06)	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)	(0.03)	(0.02)	(0.07)
Higher education	0.310***	0.313***	0.460***	0.300***	0.326***	0.276***	0.801***	0.701***	0.371***	0.296***	0.303***	0.220*
	(0.06)	(0.03)	(0.07)	(0.05)	(0.03)	(0.03)	(0.12)	(0.09)	(0.05)	(0.04)	(0.04)	(0.08)
Experience	0.014***	0.021***	0.021***	0.026***	0.007**	0.022***	0.020***	0.032***	0.016***	0.019***	0.022***	0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.000**	-0.000**	-0.000**	-0.000**	-0.000	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Full-time	-0.081	0.035**	-0.077	0.157**	-0.241***	0.002	-0.113	0.008	-0.109**	0.082***	0.157***	0.105
	(0.04)	(0.01)	(0.13)	(0.05)	(0.06)	(0.02)	(0.08)	(0.06)	(0.03)	(0.02)	(0.04)	(0.06)
Permanent contract	0.185**	0.150**	0.218***	0.027	0.254***	0.168***	0.120**	0.106***	0.329***	0.112***	0.175***	-0.054
	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.05)
Married	0.029	0.011	0.145**	0.138***	0.093***	0.069***	0.117***	0.030	0.101***	0.082***	0.081***	0.141***
	(0.03)	(0.02)	(0.05)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)
Brains	0.574***	0.587***	0.618***	0.568**	0.291***	0.476***	0.596*	0.431**	0.551***	0.635***	0.600***	0.937***
	(0.09)	(0.05)	(0.15)	(0.15)	(0.07)	(0.10)	(0.21)	(0.14)	(0.13)	(0.13)	(0.12)	(0.13)
Brawns	-0.266***	-0.280***	-0.358**	-0.191	-0.319***	-0.251**	-0.689***	-0.468**	-0.350***	-0.284**	-0.275**	-0.160
	(0.05)	(0.04)	(0.12)	(0.10)	(0.04)	(0.07)	(0.12)	(0.13)	(0.07)	(0.08)	(0.08)	(0.09)
Constant	1.934***	1.697***	1.512***	1.685***	1.951***	1.587***	1.217***	1.171***	1.609***	1.542***	1.459***	1.851***
	(0.09)	(0.08)	(0.15)	(0.12)	(0.07)	(0.11)	(0.13)	(0.13)	(0.11)	(0.14)	(0.11)	(0.17)
R-squared	0.247	0.353	0.429	0.363	0.438	0.360	0.581	0.516	0.508	0.465	0.405	0.363
Number of obs.	2947	4412	2627	2957	4668	13588	3696	3507	4274	9641	6803	1082

Notes: i) 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; part-time for employment status; temporary for type of contract and single for marital status.

Table E.4: Robustness Check: Wage Regression Estimates, Returns to Brains/Brawns

	Austria		Ireland		Italy		Portugal		Spain		UK	
	1995	2009	1995	2009	1995	2009	1995	2009	1995	2009	1995	2009
Female	-0.256***	-0.196***	-0.240***	-0.128**	-0.133***	-0.123***	-0.218***	-0.220***	-0.204***	-0.141***	-0.257***	-0.214***
	(0.05)	(0.04)	(0.05)	(0.04)	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)	(0.02)	(0.04)	(0.05)
Secondary education	0.181**	0.177***	0.264***	0.111	0.186***	0.145***	0.396***	0.283***	0.263***	0.170***	0.151***	0.068
	(0.05)	(0.03)	(0.04)	(0.06)	(0.02)	(0.03)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.10)
Higher education	0.421***	0.440***	0.511***	0.387***	0.409***	0.365***	0.960***	0.762***	0.574***	0.428***	0.382***	0.349*
	(0.08)	(0.04)	(0.07)	(0.07)	(0.04)	(0.06)	(0.16)	(0.14)	(0.09)	(0.08)	(0.06)	(0.12)
Experience	0.015***	0.023***	0.034***	0.034***	0.013***	0.029***	0.028***	0.035***	0.027***	0.026***	0.027***	0.021***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.000**	-0.000***	-0.001***	-0.000***	-0.000**	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ratio Brains/Brawns	0.046***	0.038**	0.065***	0.053**	0.047***	0.034**	0.077***	0.061***	0.053***	0.047**	0.047**	0.054**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Constant	1.985***	1.832***	1.539***	1.867***	1.815***	1.690***	0.914***	1.060***	1.545***	1.667***	1.817***	2.153***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.11)
R-squared	0.203	0.301	0.399	0.318	0.356	0.305	0.525	0.501	0.400 ¿	0.413	0.338	0.256
Number of obs.	2947	4412	2627	2957	4668	13588	3696	3507	4274 ¿	9641	6803	1082

Notes: i) 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; part-time for employment status; temporary for type of contract and single marital status.

Table E.5: Robustness Check: Returns to Skills Using Measures Constructed by PCA

	Austria		Ireland		Italy		Portugal		Spain		UK	
	1995	2009	1995	2009	1995	2009	1995	2009	1995	2009	1995	2009
Female	-0.267***	-0.195***	-0.261***	-0.125**	-0.142***	-0.115***	-0.238***	-0.226***	-0.211***	-0.140***	-0.258***	-0.157***
	(0.05)	(0.03)	(0.05)	(0.03)	(0.02)	(0.02)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Secondary education	0.109*	0.103***	0.214***	0.087	0.128***	0.105***	0.260***	0.225***	0.191***	0.130***	0.112***	0.001
	(0.04)	(0.02)	(0.03)	(0.06)	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)	(0.03)	(0.02)	(0.08)
Higher education	0.322***	0.311***	0.473***	0.319***	0.361***	0.277***	0.815***	0.697***	0.423***	0.306***	0.291***	0.209*
	(0.06)	(0.04)	(0.08)	(0.05)	(0.04)	(0.03)	(0.12)	(0.09)	(0.05)	(0.04)	(0.04)	(0.09)
Experience	0.016***	0.024***	0.032***	0.031***	0.012***	0.029***	0.027***	0.037***	0.025***	0.027***	0.026***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000*	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***	-0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Brains	0.140***	0.144***	0.167***	0.162***	0.077**	0.118***	0.144*	0.104**	0.152***	0.159***	0.167***	0.239***
	(0.02)	(0.01)	(0.03)	(0.04)	(0.02)	(0.02)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Brawns	-0.073**	-0.065***	-0.086	-0.035	-0.112***	-0.062*	-0.204***	-0.131**	-0.118***	-0.068*	-0.061*	-0.016
	(0.02)	(0.01)	(0.04)	(0.04)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Constant	2.163***	2.009***	1.749***	2.050***	1.963***	1.820***	1.180***	1.215***	1.768***	1.841***	1.959***	2.355***
	(0.05)	(0.05)	(0.07)	(0.08)	(0.02)	(0.05)	(0.07)	(0.06)	(0.04)	(0.05)	(0.03)	(0.08)
R-squared	0.231	0.347	0.404	0.340	0.364	0.333	0.569	0.510	0.436	0.450	0.383	0.346
Number of obs.	2947	4412	2627	2957	4668	13588	3696	3507	4274	9641	6803	1082

Notes: i) 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; part-time for employment status; temporary for type of contract and single for marital status.

Table E.6: Robustness Check: Decomposition of the changes in gender wage gap using PCA skill measures, 1995 vs 2009

Panel A	ΔGender Wage Gap (I)	ΔObserved Quantities (II)	ΔObserved Prices (III)	ΔUnobserved Quantities (IV)	ΔUnobserved Prices (V)
Austria	-0.068	-0.010	-0.005	-0.050	-0.003
Ireland	-0.156	-0.063	0.023	-0.105	-0.011
Italy	-0.030	-0.053	0.051	-0.035	0.008
Portugal	-0.033	-0.073	0.047	-0.013	0.006
Spain	-0.019	0.003	0.043	-0.030	-0.034
UK	-0.052	0.041	0.029	-0.130	0.007

Panel B	ΔGender Wage Gap (I)	Part Explained by Brains and Brawns (II)	Contribution of ΔBrains and ΔBrawns (III)	Contribution of ΔPrices of Brains and Brawns (IV)
Austria	-0.068	-0.022	-0.012	-0.010
Ireland	-0.156	-0.001	-0.015	0.014
Italy	-0.030	0.014	-0.016	0.030
Portugal	-0.033	0.009	-0.012	0.021
Spain	-0.019	0.028	0.009	0.019
UK	-0.052	0.062	0.018	0.044