The gender wage gap in Europe: The role of gender convergence, job preferences and distributional effects

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Draft 15th June 2017

Abstract

While the gender wage gap has declined in magnitude over time, the gap that remains is largely unexplained due to gender convergence in key wage determining characteristics. In this paper we show that the degree of gender convergence differs across countries in Europe. Most if not all of the wage gap is unexplained in some countries, predominantly in Eastern Europe, while in some central and peripheral countries, differences between the characteristics of males and females can explain a relatively large proportion of the gap. We investigate whether gender differences relating to job motives play a role in explaining the gender wage gap. We find that females are more motivated than males to find a job that is closer to home and offers job security, whereas males are more motivated by money. Males are found to earn, on average, 12 percent more than females and gender differences in job motives are associated with a 1.4 percentage point increase in the wage gap. Job motives explain more of the wage gap than characteristics relating to age, tenure and previous employment status. A quantile decomposition reveals a U-shaped wage gap which starts off high at the lower end of the wage distribution, reduces towards the median and increases again at the upper end of the distribution, with the role of job motives being relatively strong at the upper end of the wage distribution.

1. Introduction

Studies of the gender wage gap often apply decomposition techniques to investigate how much of the wage difference is due to differences in observed characteristics of men and women and how much is due to different rates of return for those same characteristics. There has been a general decline in the magnitude of the gender wage gap over time. However, the portion of the gender wage gap explained by differences in characteristics between genders has also declined, as educational attainment and labour force participation of women and men have converged (Blau and Kahn, 2006 & 2016; Goldin,2014). Therefore, observable differences in key wage determining characteristics such as educational attainment and job tenure are becoming less important in explaining gender wage differentials. This leads to the question of whether there are other observable factors that could potentially explain at least a portion of the remaining differential that have so far been under-researched within the literature. In this context the role of compensating differentials may represent one component of the "final chapter" of gender pay equality (Goldin, 2014). Many high paying jobs require individuals to spend long hours in the office. This type of work can be incompatible with family life, especially with young children, thereby forcing individuals who are, or expect to be, caregivers to trade-off job characteristics such as higher earnings for others that facilitate a more flexible work-family balance. Given that females are still expected to play the primary care giving role in many households, compensating wage effects are potentially an important factor in explaining the remaining wage gaps observed in most developed countries. Any finding that trade-offs in job characteristics are a determining factor in the gender pay gap will also have important policy implications. Goldin (2014) suggests that policies which change how jobs are structured, such as greater flexibility, could reduce the gender wage gap and Huffman et al. (2017) find that policies which facilitate a better work-family balance, such as workplace childcare, can help reduce gender wage inequality.

While compensating wage differentials are often highlighted as a potential explanation for the gender pay gap, as in Blau and Kahn (2016) and Goldin (2014), there is relatively little empirical evidence for this. The reason is that compensating differentials are difficult to measure and are not directly captured in most labour force surveys. In this paper we utilise the 2014 European Skills and Jobs Survey (ESJS) which, in addition to capturing detailed information on wages, human capital and job characteristics, captures information on the motives affecting the individual's current job choice. In the absence of a direct measure of compensating differentials, utilising data which directly captures individuals' motives for accepting their current jobs may be informative. Specifically, the mechanism through which compensating differentials impacts the wage gap should be reflected by different job motives, which vary by gender, and this is what our data reveals. We find that females place greater value than males on jobs that are close to home and offer good security, and these job motives are associated with lower wages. However, males put a stronger emphasis on the pay and benefits package compared to females. This is consistent with the theory of compensating differentials, whereby females trade off higher wages for other types of job characteristics, some of which may reflect the influence of family obligations in a female's job choice. This is supported by the findings of Mas and Pallais (2016) who use a field experiment to study compensating differentials. They find that females, particularly those with children, are more willing than men to trade off higher wages in order to work from home and to avoid disruptions to their work schedule. While they don't directly investigate the role of compensating differentials on the wage gap, Mas and Pallais (2016) suggest that compensating differentials alone are unlikely to fully explain the gender wage differential.

In terms of the previous literature, presumably driven by a lack of data, relatively few studies have directly measured the role of gender based differences in job motives on the gender wage gap. In related work, McGuinness et al. (2011) assess the role of motivations in explaining the gender wage gap among part-time workers in Ireland. Their data has information on the reasons why people work part-time, due to either; disability, cannot find full-time work, family commitments, financially secure, earn enough working part-time and other reasons. They find a significant difference between the reasons for working part-time between men and women, with most women indicating family commitments and men typically reporting that they cannot find full-time work. Incorporating these motives into a decomposition of the part-time gender wage gap substantially reduces the unexplained component.

Other studies have used motivational values to approximate the role of decisions around job choice on the gender pay gap. Swaffield (2007) finds that controlling for attitudes relating to work-home orientation, family related labour constraints and labour market aspirations reduces the gender pay gap. However, these are broad attitudinal controls and as such, do not directly relate to an individual's motivations for accepting a job. Similarly, Chevalier (2004) uses a UK dataset which captures information on a person's long-term values, such as career development, job satisfaction, status and respect as well as information on people's self reported level of ambition and finds that these factors play a role in explaining the gender wage gap. Earlier work by Filer (1985) uses the 1977 Quality of Employment Survey in the US to investigate the role of compensating differentials in the gender wage gap. Filer (1985) found that some of the wage gap was explained by men and women holding jobs with substantially different working conditions.

Given that our research question examines the effect of factors that lie outside the standard human capital framework on gender pay differentials, i.e. job motives, it is also worth noting other aspects of the literature that have sought to explore alternative explanations that can potentially account for the unexplained gap in earnings. Some studies suggest women may be less competitive than men and therefore underrepresented in competitive jobs (Niederle and Vesterlund, 2007) or are less effective at bargaining for higher pay than males (Babcock and Laschever, 2003). However, Manning and Saidi (2010) indicate a limited role for these competition effects in explaining the gender wage gap. In recent work, Quintana-Garcia and Elvira (2017) study the effects of external labour market hiring on the compensation of males and females in management positions. They find that women who are hired externally face a disadvantage in terms of compensation and provide evidence that this disadvantage may be mitigated by having more females in top management positions. Huffman et al. (2017) examine the effects of organizational practices which target gender inequality, such as workplace childcare, on gender wage inequality. They find that these types of policies generate a modest reduction in gender wage inequality, especially at the lower end of the distribution.

The remainder of the paper is organized as follows. Section 2 describes the data and presents some descriptive statistics. Section 3 outlines the methodology and Section 4 presents the results. Section 5 concludes.

2. Data and descriptive statistics

The data used in this study comes from the 2014 European Skills and Jobs Survey (ESJS) and contains information on 48,000 adult employees (aged 24 to 65) in 28 EU member states. It was financed and developed by the European Centre for the Development of Vocational Training (Cedefop), in collaboration with a network of experts on skills, the OECD and Eurofound (Cedefop, 2015). Respondent information is collected on a range of human capital attributes (including education levels and job tenure), personal characteristics (including gender, age and sector) as well as wage data. Exact wage data is provided for 70 percent of the sample. Some individuals did not give precise wage data, so the remaining 30 percent of wage data is in wage bands. In our analysis, we use the midpoint of these wage bands for this 30 percent of individuals. However, we verify the robustness of our results using only the 70 percent who reported exact wages. Ten of the countries in the sample do not use the euro currency. For these countries, we converted wages to euros using exchange rates from the 7th of March 2014, which coincides with the data collection time frame.

In terms of the key information reflecting job motives, the survey asks individuals to rank the importance of the following nine job-related characteristics on their decision to accept their current job; 1. the job suited your qualifications and skills, 2. you wanted to gain some work experience, 3. the job provided security, 4. the job offered good career progression/career development, 5. the company/organisation was well known/respected in its field, 6. the pay and package of benefits (e.g. health insurance, bonuses, company car etc.) was good, 7. the job was close to home, 8. you were interested in the nature of the work itself, 9. the job had a good work-life balance. Individuals rank the importance of each motivating factor on a scale of 1 to 10, with 10 being most important. The questions are not mutually exclusive and respondents are asked to provide a rating for each job attribute.

At a descriptive level there are gender differences in the motives reported by individuals for accepting their current jobs. Table 1 below uses two statistics to show the differences between males and females for each of the nine job motives. The first shows the mean score for males and females for each motive. For example, on average, males assign a score of 6.64 (out of 10) to pay and benefits, whereas for females this is 6.40. The second statistic involves calculating a person's relative score for each motive; a person's overall mean ranking for the nine motives is calculated and this is subtracted from the score given to the individual motive. Therefore, a positive number indicates that a person values the motive above average and vice versa. The average relative score for males and females is then calculated. Again taking pay and benefits as an example, while on average both males and females assign a below average score to benefits and pay, it is clear that this factor is a more important consideration for males when choosing a job; the score given to benefits and pay for males is 0.39 below their average score for all motives, whereas for females it is 0.78 below average. The data suggests that males place greater importance on career progression and the reputation of the organisation, with the latter being of above average importance to men but below average for women. These descriptive statistics are consistent with the findings of Chevalier (2004) who shows that that males are typically more self-orientated and career driven than women. Job attributes such as job security, being close to home, gaining work experience and work-life balance are more important for women than men when it comes to choosing a job.

Table 1: Motivations for accepting a job

	Average score			Relative score		
Motive	**Female**	**Male**	**Diff**	**Female**	**Male**	**Diff**
Benefits	6.40	6.64	***	-0.78	-0.39	***
Security	7.98	7.61	***	0.78	0.56	***
Experience	7.18	6.78	***	-0.01	-0.25	***
Career	6.67	6.71		-0.49	-0.32	***
Reputation	7.14	7.15		-0.05	0.12	***
Close to home	6.58	6.32	***	-0.61	-0.69	***
Work-life	7.50	7.23	***	0.30	0.20	***
Suits skills	7.40	7.21	***	0.20	0.16	*
Like the work	7.86	7.68	***	0.66	0.63	*

Note: The stars in the Diff column indicate whether the difference in average motives between males and females is statistically significant. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The averages of key wage determining characteristics such as educational attainment, age and job tenure are reported for males and females in Table 2. The results in Table 2 are broadly supportive of the gender convergence phenomenon highlighted by Blau and Kahn (2006 & 2016) and Goldin (2014). Male and female full-time employees look similar in relation to their age, job tenure and previous labour status. The reversal in the gender education gap is apparent, given that average educational attainment of females is higher; 53 percent of females are educated to tertiary level compared to 43 percent of males. Gender differences remain when it comes to the percentage of employees working in the private sector (56 percent for females versus 70 percent for males).

Table 2: Characteristics of males and females

	Female	**Male**
Age	41.51	42.57
Educational attainment		
Low	0.09	0.14
Medium	0.38	0.43
High	0.53	0.43
Job-related		
Job tenure	10.13	10.85
Private sector	0.56	0.70
Previous status		
Employed	0.59	0.64
Self employed	0.03	0.04
In education	0.20	0.18
Unemployed	0.13	0.12
Other	0.05	0.02

3. Methodology

Our analysis is based on the following wage regression,

$$\ln Wage_{i,j} = \alpha + \beta_1 H_{i,j} + \beta_2 M_{i,j} + \varepsilon_{i,j} \quad (2)$$

where the log hourly wage of individual *i* in country *j* is regressed on a vector of personal and human capital variables ($H_{i,j}$), including; gender, age, education level, job tenure, previous employment status (employed, self-employed, in education or unemployed) and sector (public or private). $M_{i,j}$ is a vector of the nine job-choice attributes outlined above. The coefficient on gender from an OLS regression of equation (2) gives an estimate of the gender wage gap, controlling for other personal and human capital characteristics and job motives. Our baseline specification does not include occupation controls as these will be correlated with education, however, as a robustness check we report the results from a specification which includes occupation, showing that it does not change our main results.

Based on our wage regression, we carry out an Oaxaca-Blinder decomposition on the difference in the average wage of males and females. For ease of exposition, let $X_{i,j}$ be a vector which includes both personal and human capital variables ($H_{i,j}$) and job-related motives ($M_{i,j}$). The Oaxaca decomposition yields,

$$\bar{W}_m - \bar{W}_f = (\bar{X}_m - \bar{X}_f)\hat{\beta}_{1m} + (\hat{\beta}_{1m} - \hat{\beta}_{1f})\bar{X}_f \quad (3)$$

where the average wage difference between men and women ($\bar{W}_m - \bar{W}_f$) is decomposed into an explained part due to differences in characteristics, $(\bar{X}_m - \bar{X}_f)\hat{\beta}_{1m}$, and an unexplained part due to differences in coefficients, $(\hat{\beta}_{1m} - \hat{\beta}_{1f})\bar{X}_f$. In addition to decomposing the average differential into an explained and unexplained component, we present detailed results showing the contribution of each individual covariate. This allows us to establish which of the independent variables, including the nine job motives, may be most important in explaining the observed gender wage gap.

We decompose the gender wage gap using the entire sample of full-time workers from all 28 countries, before proceeding to decompose the wage gap for each country individually. It is important to note that the raw wage differential $\bar{W}_m - \bar{W}_f$ from the full sample can be influenced by distributional differences in the sampling of males and females across countries with different wage structures. To see this, consider a scenario where we have one high wage country (H) and one low wage country (L). Suppose we survey 10 males and 10 females from country H and find that everybody earns €1000 per week. In country L, we survey 10 males and 20 females, each of which earns €100 per week. Clearly, there is no gender wage gap but because there is a relatively large number of females from the low income country, this will drag down the average female wage, so that the average male wage is €550 but the average female wage is €400. As such the raw wage differential is €150. However, when decomposing the wage differential using the entire sample, we include country dummy variables in our wage regression. The endowment effect associated with the country dummy variables captures the component of the raw differential that is due to this type of sampling issue. For example, let *D* be a dummy variable indicating the low wage country. The endowment effect associated with this variable is $(\bar{D}_m - \bar{D}_f)\hat{\beta}_m$. Relating this to our hypothetical example, assuming the only independent variable is the country dummy, gives $(\bar{D}_m - \bar{D}_f)\hat{\beta}_m = \left(\frac{1}{2} - \frac{2}{3}\right) - 900 = -150$. Therefore, the endowment effect of the country dummies captures the component of the raw gap that is explained by differences in the distribution of males and females across countries. As such, when reporting the raw wage differential from the full sample, we adjust it by subtracting the endowment effects from the country dummy variables. This pooled approach ensures that the reported raw wage gap is a true reflection of the wage gap across the 28 countries. This approach is equivalent to estimating country specific decompositions and averaging the results. Including all countries in this way allows us to utilise our full sample. In addition to the pooled analysis, we also decompose the wage gap separately for each country in the sample.

While the Oaxaca technique allows us to decompose the gender wage gap at the mean, it does not allow us to assess the degree to which the gender pay gap, or the factors that determine it, vary across the wage distribution. A priori we might expect that the cost of making compromises becomes more substantial for more highly educated and skilled females who are typically located in the upper quantiles of the earnings distribution. To address this issue we employ a technique proposed by Firpo et al. (2009) that allows us to decompose the wage gap across the entire wage distribution. In a standard OLS regression, the β coefficient can be interpreted as the effect of a change in x on the unconditional mean of y. As such, OLS regressions can be used in the Oaxaca decomposition to examine the unconditional mean difference in gender wages. However, the β coefficient from a quantile regression of y on x gives the effect of a change in x on the conditional quantile, not the unconditional quantile, thereby making the unconditional quantile decomposition less straightforward than a standard Oaxaca decomposition of the unconditional mean. The method proposed by Firpo et al. (2009) overcomes this difficulty. The technique can be outlined in three stages. The first stage involves calculating the recentered influence function (RIF) of the unconditional quantile of the dependent variable. Denoting q_τ as the τth quantile of interest, the RIF is derived by first calculating the influence function (IF) as follows,

$$IF = (\tau - 1\{Y \leq q_\tau\})/f_Y(q_\tau)$$

where Y denotes the dependent variable, in our case log wages, $f_Y(q_\tau)$ is the density at point q_τ and $1\{Y \leq q_\tau\}$ is a dummy variable indicating whether Y is less than or equal to q_τ. To get the RIF, one adds back the quantile to the IF, such that, $RIF = q_\tau + IF$.

In the second stage, the RIF is then used as a dependent variable in the wage regression, instead of $lnWage_{i,j}$. The resulting β from the RIF regression captures the marginal effect of a change in x on the unconditional quantile of y. Finally, in the third stage, a standard Oaxaca decomposition is carried out on the RIF regression, which yields the unconditional quantile decomposition. While other quantile decomposition techniques exist, an advantage of the Firpo et al. (2009) technique is that it allows for a detailed decomposition to be carried out in a straightforward way. For a detailed explanation of decomposition methods, see Fortin et al. (2011).

4. Results

The results from an OLS regression of equation (2), including country dummy variables, are shown in Table 3. The model is well specified and all the coefficients behave as expected. The coefficient on the male variable is the estimate of the gender wage gap, indicating that the hourly wage of males is 12.6 percent higher than females with comparable characteristics. Age, education and job tenure, measured as the number of years the individual has been working for their current employer, all have positive, statistically significant effects on wages. A one year increase in age and tenure are associated with an increase in wages of 0.3 and 1 percent respectively. Having a high level of education is associated with a 43 percent increase in wages relative to a low education.[1] Previous employment status before the current job also affects wages; relative to being previously in employment, being previously unemployed, in education or "other" is associated with a reduction in wages of 13 percent, 3.9 percent and 8.3 percent respectively. Being previously self-employed (relative to being employed) has no statistically significant effect.

The OLS regression also shows that there are some earnings impacts associated with individuals' motives for accepting their current jobs. Perhaps not surprisingly, the job motive associated with the largest positive effect on wages is benefits and pay. Career progression and finding a job that suits one's skills are also associated with increased wages, albeit to a lesser extent. However, being motivated to find a job that is close to home, offers good security or for the purposes of gaining work experience is associated with lower wages. Being motivated by a good work-life balance and finding work that is intrinsically desirable are both associated with a small positive effect on wages, while the motive relating to the reputation of the organisation has no effect. Therefore, in summary, while the marginal effects associated with job motives are lower than those related to human capital endowments, they do influence earnings. Nevertheless, the results related to potential areas where females are more likely to compromise on job choice are somewhat mixed. While decisions to accept jobs for reasons of job security and proximity to home have negative earnings effects, jobs that were chosen to facilitate increased work life balance have a positive, albeit small, impact on pay.

[1] High education relates to tertiary education, medium education to upper secondary or post-secondary (including vocational) but not tertiary.

Table 3: Wage Regression: Euro 28 2014

VARIABLES	Spec (1)
Male	0.126***
	(0.006)
Age	0.003***
	(0.000)
Medium education	0.185***
	(0.011)
High education	0.432***
	(0.011)
Job tenure	0.010***
	(0.000)
Private sector	0.009
	(0.007)
Previous status	
Self employed	-0.002
	(0.017)
In education	-0.039***
	(0.009)
Unemployed	-0.130***
	(0.010)
Other	-0.083***
	(0.018)
Job motives	
Suit skills	0.010***
	(0.001)
Gain experience	-0.007***
	(0.001)
Security	-0.008***
	(0.002)
Career progression	0.014***
	(0.002)
Reputation of firm	0.001
	(0.002)
Benefits and pay	0.019***
	(0.001)
Close to home	-0.015***
	(0.001)
Like the work	0.004**
	(0.002)
Work-life balance	0.004**
	(0.001)
Constant	2.153***
	(0.037)
Country FE	Yes
Observations	29,181
R-squared	0.637

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.1 Oaxaca decomposition

The summary of the Oaxaca decomposition for the full sample is shown in Table 4. The raw differential indicates that average male wages are approximately 12 percent higher than average female wages for full-time workers in Europe. In both specifications, the overall explained component is small. This is consistent with previous work by Christofides et al. (2013) who, using 2007 EU-SILC data, find that most, if not all, of the gender wage gap in Europe is unexplained. However, while the Oaxaca decomposition shown in Table 4 shows overall net explained and unexplained components, a detailed decomposition, shown in Table 5, is necessary to gain information on the relative importance of individual covariates. Even though the overall explained component is small, or zero, some variables may be increasing the gap while others are decreasing the gap. The top half of the table groups the variables into categories including age, education, job-related (tenure and public / private sector), previous employment status, job motives, occupation and country effects. The endowment and coefficient effects, reported as percentage point contributions to the overall wage gap, are shown for each group of variables. Below this is a more disaggregated decomposition showing the endowment and coefficient effects for each individual covariate. The detailed decomposition provides some insights as to the low overall explained component of the gender wage gap. While gender differences in characteristics relating to job motives, age, previous employment status, tenure and sector (public / private) increase the wage gap, differences in educational attainment between genders offsets some of this by reducing the wage gap. The explained component relating to education is relatively large and reflects the fact that female educational attainment is generally greater than male attainment, and higher education is associated with higher wages. This is consistent with Blau and Kahn (2016) who document a reversal in the gender education gap since the 1980's.

Table 4: Oaxaca decomposition

	Spec (1)	Spec (2)
Raw Differential*	12.4	12
Explained	-0.2	0.4
Unexplained		
Due to coefficients	2.8	0.2
Due to shift coefficient	9.8	11.4

Note: Occupational controls are included in Spec (2).

Table 5: Detailed Oaxaca decomposition

	Spec (1)		Spec (2)	
Categories	Explained	Unexplained	Explained	Unexplained
Age	0.4	-0.4	0.3	-0.8
Education	-3.4	-0.6	-1.9	-0.4
Job-related	1.1	4.4	1.1	4.3
Prev employment status	0.3	-1.3	0.3	-1.1
Job motives	1.4	-1.8	1.2	-0.8
Occupation	-	-	-0.6	-2.1
Country effects	-	2.5	-	1.1
Total	**-0.2**	**2.8**	**0.4**	**0.2**

Variables	Explained	Unexplained	Explained	Unexplained
Age	0.4	-0.4	0.3	-0.8
Low education	-1	0.1	-0.6	0
Medium education	-0.1	0	0	0.4
High education	-2.3	-0.7	-1.3	-0.8
Job tenure	0.8	2.5	0.7	3
Private sector	0.3	1.9	0.4	1.3
Prev employed	0.2	-1.1	0.2	-1
Prev self-employed	0.1	0	0.1	0.1
Prev education	0	-0.2	0	-0.2
Prev unemployed	0	-0.1	0	-0.1
Prev other	0	0.1	0	0.1
Suits skills	-0.2	2.8	-0.1	3.6
Gain experience	0.4	-2.4	0.4	-3
Security	0.5	-6.5	0.3	-5.7
Career progression	0	-0.2	0	-0.1
Reputation of firm	0	-0.1	0	-0.8
Benefits and pay	0.5	3.6	0.5	3.3
Close to home	0.4	-0.8	0.3	-0.4
Likes the work	-0.1	-0.8	0	-0.9
Work-life balance	-0.1	2.6	-0.2	3.2
Managers	-	-	0.8	-0.2
Professionals	-	-	-1.3	-0.2
Assocprof	-	-	0.5	-0.2
Sales	-	-	0.5	-0.4
Clerical	-	-	-0.1	-1.6
Building	-	-	-0.5	0.2
Machineop	-	-	-0.3	0.1
Elementary	-	-	-0.1	0.2
Agriculture	-	-	-0.1	0
Country effects	-	2.5	-	1.1
Total	**-0.2**	**2.8**	**0.4**	**0.2**

Note: Occupational controls are included in Spec (2).

Differences in job motives between males and females account for a 1.4 percentage point increase in the gender wage gap, which equates to 11.3 percent of the total raw gender pay differential. This is relatively large compared to the explained component of other categories, such as job-related variables (1.1 percentage points) and previous employment status (0.3 percentage points). This result is robust to the inclusion of occupational controls. The disaggregated decomposition reveals that job motives relating to benefits and pay, being close to home, job security and work experience are of particular importance, with these four motives alone contributing 1.7 percentage points to the wage gap. This reflects the fact that females, on average, place greater importance on being close to home, gaining work experience and job security, all of which are negatively associated with wages, while males place greater importance on benefits and pay which is positively associated with wages. Differences in job motives relating to intrinsically liking the work, accepting a job that suits one's skills and work-life balance, negatively contribute, i.e., lowers the wage gap, by 0.4 percentage points. The endowment effect relating to educational attainment lowers the wage gap by 3.4 percentage points, which reflects the fact that educational attainment of females in the sample is higher than that for males, and higher education is associated with higher pay. The endowment effect relating to occupational tenure is small, explaining just 0.8 percentage points of the wage gap. This indicates that female employees included in the sample do not appear to be taking large periods of time out of the labour market or occupationally downgrading to have children. This is consistent with the descriptive evidence presented in Table 2 which showed that average occupational tenure of males and females was quite similar; 10.13 years for females and 10.85 years for males.

The job motive results are in line with the theory of compensating differentials, with females placing greater value on finding jobs that are close to home, provide good security and offer work experience. The result relating to job security has support in the field experiment carried out by Mas and Pallais (2016), where females were willing to trade off higher pay for a more secure working schedule. Males on the other hand, are more motivated by benefits and pay.

Overall, the unexplained component (the coefficient effects) from the various explanatory variables increase the wage gap by 2.8 percentage points. In addition, the difference between the shift coefficient amounts to 9.8 percentage points and therefore, the overall effect amounts to 12.6 percentage points of the wage gap.

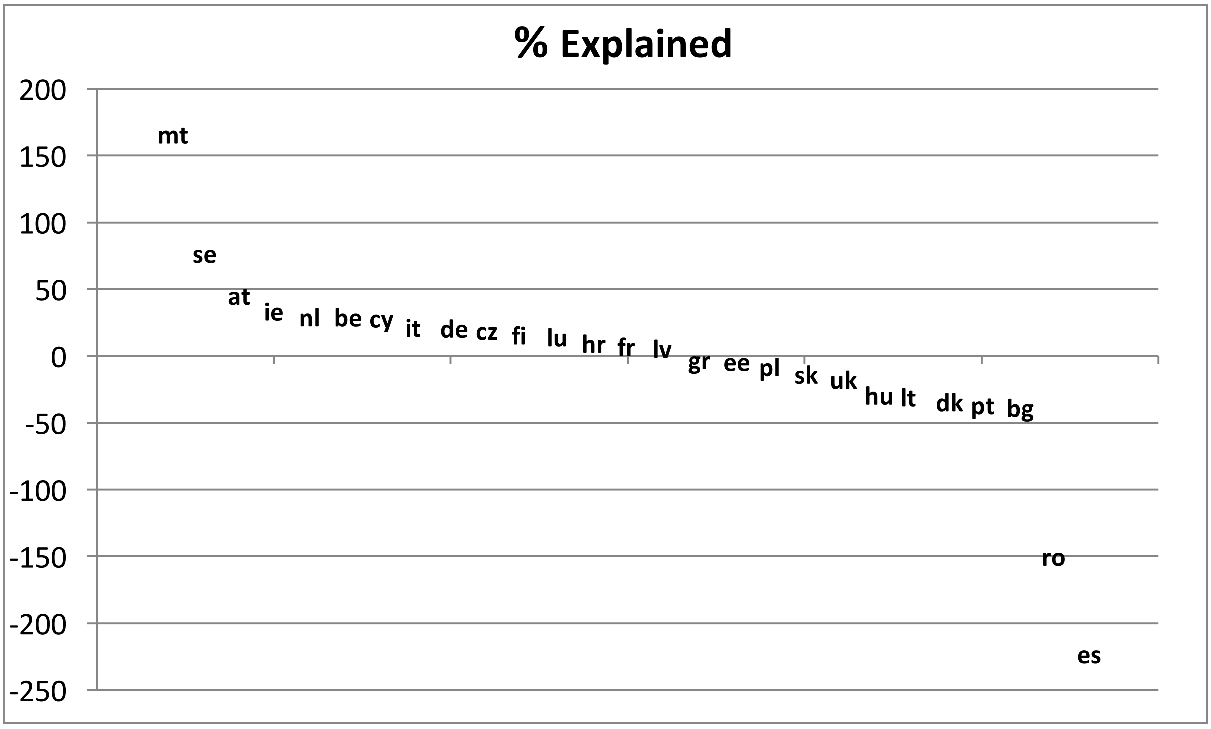
The unexplained components (the coefficient effects) relating to the job motives suggest the costs for making trade offs tend to be lower for females than males. For example, the unexplained component relating to both job security and being close to home are negative. This is due to the fact that, while both factors are associated with lower wages for both genders, the negative wage effect for males is more pronounced than females. Conversely, the job attributes that tend to boost earnings such as pay and benefits, skills suitability and work life balance are associated with higher returns for males. There is also a sizeable unexplained component associated with job-related covariates that also work to the benefit of male employees; differences between genders in the wage returns relating to employment tenure and working in the private sector increase the wage gap by 2.5 and 1.9 percentage points respectively.

While the analysis so far has been useful in understanding the gender wage gap across the full sample of countries, there is variation between countries that can only be explored by focusing on each country individually. In Appendix Table A1 we show the results of Oaxaca decompositions for every country in the sample, along with a detailed decomposition where we group variables in the same way as in Table 5. Estonia has the highest raw gender wage differential in the EU at 33.4 percent. This is consistent with previous work by Osila (2015) who examines the gender wage gap in Europe using EU-LFS data. Other countries with above average raw gender wage differentials include Latvia (25%), Czech Republic (21%), Luxembourg (20.5%), Austria (20.3%), Finland (18.6%), Ireland (17.6%), Portugal (16.1%), Hungary (15.3%), Slovakia (15.3%), Bulgaria (15%), Germany (14%) and Belgium (13.4%). While most of the gender wage gap remains unexplained across these countries, a sizeable percentage of the gap is explained in countries such as Sweden (77%), Austria (45%), Ireland (34%), Belgium (29%) and the Netherlands (29%). Figure 1 shows the percentage of the gender wage gap explained in each of the countries in the sample. All but three of the countries fall in the range of +100 to -100 percent, however, Malta, Romania and Spain are outliers which is a result of their low raw wage differentials. In Malta and Spain the raw gender wage differentials are just 2.1 percent and 1.3 percent respectively, with explained components amounting to 3.5 percentage points (or 167 percent) in Malta and -2.9 percentage points (223 percent) in Spain. The raw differential is larger in Romania at 6.2 percent, with a negative explained component of -9.3 percentage points (150 percent).

To the extent that a zero or negative explained component is consistent with the notion of gender convergence, the results would suggest that this has occurred predominantly, but not exclusively, in Eastern European countries. For example, in Romania, Bulgaria, Lithuania, Hungary, Slovakia, Poland, Estonia, Latvia and Croatia, the explained component is either very close to zero or negative. Therefore, in these countries, the male gender wage premium cannot be explained by females having lower levels of wage enhancing characteristics compared to males. However, the explained component is larger in countries such as Germany, Italy, Belgium, Netherlands, Ireland and Austria, which indicates that in these countries, females and males are still quite different in their wage enhancing characteristics and this can explain some of the gender wage gap.

Finally, reflecting the varying role of observable characteristics generally in explaining the raw wage gap, differences in job motives between males and females plays a role in explaining some of the gender wage gap in all of these countries, but to varying degrees; expressed as a percentage of the raw wage gap, job motives explain approximately 10 percent, on average, of the wage differential. Job motives play a particularly strong role in explaining the gender wage gap in countries with an above average pay gap. For example, job motives expressed as a percentage of the raw wage differential amount to; Hungary (17%), Czech Republic (15%), Portugal (14%) and Ireland (12%). However, job motives also play a role in explaining the gender wage gap in countries with lower raw wage differentials; France (11%), Poland (10%), Cyprus (10%), Sweden (9%), Croatia (9%) and Italy (8%). The explained component relating to job motives is negative in five of the fifteen countries with below average gender wage gaps; UK, Netherlands, Greece, Romania and Slovenia, which is also the only country in the sample with a negative wage gap, with average female wages 3.4 percent higher than male wages.

Figure 1: Explained component of the gender wage gap across countries



4.2 Quantile decomposition

We next carry out quantile analysis for each decile in the wage distribution. The results of the RIF quantile regressions are shown in Table A2. The estimates show the effect of a change in each covariate on the unconditional decile of the wage distribution. In terms of the estimate of the gender wage gap (the *male* coefficient), this takes a U shape across the distribution, starting off high at the lower end of the distribution (21%) before decreasing and reaching its lowest point at the median (9%), and increasing again at the higher end of the distribution (13%). The job motive estimates show that assigning a high level of importance to benefits and pay and career progression is associated with a strong positive effect on wages across the entire distribution, while being close to home has a consistently negative effect. Being motivated by job security is negatively associated with wages at the middle and upper end of the wage distribution. Being motivated by gaining work experience is negatively associated with wages, especially around the median, while being motivated to find a job that suits one's skills is associated with higher wages, especially at the lower end of the wage distribution.

We examine differences in job motives between males and females across the wage distribution by calculating the average job motive rankings of males and females in each decile. Table A3 shows the percentage difference between males and females for each motive in each decile, with a positive figure indicating that males rank a motive higher than females. The ranking of job motives across the distribution are in line with the averages presented in Table 1. For example, males tend to be more motivated by benefits and pay across the entire distribution; males in the bottom decile assign a ranking to this motive which is 2.4 percent higher than females and 5 percent higher in the top decile. Females place more importance on motives such as being close to home, job security and gaining work experience.

The RIF quantile decomposition results are shown in Table A4. For each decile, we show the raw gender wage differential and how much of this differential can be explained by differences in endowments and how much is unexplained. As with the Oaxaca decomposition, the overall explained component is low. Gender differences relating to job motives, age, previous employment status, tenure and sector (public / private) increase the wage gap, however, differences in educational attainment between genders offset this by reducing the gap. Detailed decomposition results are shown for the explained component, in terms of the percentage point contribution to the raw differential. While the raw wage differential is relatively high at both the very bottom and top of the wage distribution, the differential is generally smaller in the top half of the distribution. However, even though the raw differential becomes smaller, the explained component, including that relating to job motives, becomes larger. For example, in decile 7, differences in the job motives of males and females add 1.5 percentage points to a raw gender wage gap of 10.3 percent. Expressed as a percentage of the raw differential, differences in job motives explain approximately 7 percent of the wage gap in the bottom half of the distribution and 13 percent in the top half. Most of the overall job motive effect is driven by four of the nine motives; benefits and pay, being close to home, gaining work experience and job security. Benefits and pay and being close to home have a strong effect across the wage distribution, adding approximately one percentage point to the raw wage gap. Motives relating to job security and work experience have a particularly large effect at the top of the wage distribution; in decile 9, gender differences in these two job motives add approximately 1.5 percentage points to the wage gap. The results indicate that difference in motives account for a non-trivial proportion of the raw gender pay gap and become increasingly important in the upper segments of the wage distribution.

5. Conclusion

The magnitude of the gender wage gap has declined gradually over time. This is partly attributable to a gender convergence in areas such as education, with females catching up with, and often overtaking, males with respect to educational attainment. Goldin describes this as a grand gender convergence (2014). However, despite this gender convergence in human capital related characteristics, a gender wage gap persists and remains largely unexplained. Compensating differentials have been suggested as a potential explanation for the remaining wage gap. High paying jobs may be inflexible, requiring employees to work long and fixed hours. If females trade off higher pay for other characteristics such as greater flexibility, job security or being close to home, this may explain some of the wage gap. However, measuring and quantifying compensating differentials is a difficult task and as such, little empirical evidence exists which investigates this issue.

By exploiting data relating to job motives contained in the European Skills and Jobs Survey, we have attempted to address this gap in the literature by examining whether job motives can explain some of the gender wage gap in Europe. Firstly, we observe that gender convergence is not a universal phenomenon with differences in observable characteristics still playing a role in explaining the raw wage gap in many central and peripheral European countries. However, gender convergence does appear more prominent within eastern European countries, with the result being that within these countries, the raw gender wage differential remains entirely unexplained as males and females are comparable with respect to wage increasing characteristics. Our results provide some support for the theory of compensating differentials. We find that males are motivated by financial benefits and pay, whereas females are more likely to be motivated by other job attributes such as being close to home and job security. Our analysis of full-time employees in Europe indicates that males are paid, on average, 12 percent more than females and differences in job motives between males and females increases the wage gap by 1.4 percentage points, accounting for over 10 per cent of the raw differential. This is primarily driven by differences in four job motives; benefits and pay, being close to home, job security and gaining work experience. The explained component relating to job motives is greater than that for age, tenure and previous employment status, indicating that motives are an important consideration in the analysis of the gender wage gap. Our quantile analysis revealed that while the raw wage gap generally gets smaller as we move up the wage distribution, the explained component relating to job motives gets larger.

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Appendix Tables

Table A1: Country Level Oaxaca Decompositions

	Oaxaca decomposition			Detailed decomposition (p.p.'s explained)				
Country	**Raw differential**	**Explained**	**Unexplained**	**Age**	**Education**	**Job-related**	**Previous status**	**Job motives**
Estonia	33.4	-1.4	34.8	1.3	-3.9	0.5	-0.4	1.1
Latvia	25	1.4	23.6	-0.9	-3.3	1.6	1.3	2.7
Czech R.	21	4	17	0.7	-1.2	2	-0.6	3.1
Luxembourg	20.5	2.9	17.6	0.6	1.4	-0.7	-0.2	1.8
Austria	20.3	9.2	11.1	2.3	0.2	3.9	1.1	1.7
Finland	18.6	2.9	16.1	1.9	-1.7	1.4	1	0.3
Ireland	17.6	5.9	11.6	3.3	-2.8	3.1	0.2	2.1
Portugal	16.1	-5.9	22	-0.1	-4.9	-1.6	-1.5	2.2
Hungary	15.3	-4.5	19.8	-0.3	-5.9	0.2	-1.1	2.6
Slovakia	15.3	-2.1	17.4	-0.4	-2.7	-0.3	0	1.3
Bulgaria	15	-5.8	20.8	0.2	-7.2	0.6	-0.3	0.9
Germany	14	2.9	11.1	0	0.1	1.8	0.1	0.9
Belgium	13.4	3.9	9.5	1.1	-4.1	4.9	0.5	1.5
France	11.3	0.8	10.5	0.8	-2.3	0.8	0.2	1.3
UK	10.2	-1.8	12	1.3	-3.7	1.3	-0.2	-0.5
Poland	9.9	-0.8	10.7	0.5	-4.3	0.6	1.4	1
Cyprus	9.9	2.8	7.1	0.1	-1	1.3	1.3	1.1
Sweden	8.6	6.6	2	4.1	-0.6	2.9	-0.6	0.8
Croatia	8.5	0.8	7.7	0.6	-1.6	0.1	-0.4	2.1
Italy	7.5	1.6	5.9	3.4	-3	0.4	0	0.8
Netherlands	7.2	2.1	5.1	5.4	-6.2	3	1	-1.1
Greece	7.1	-0.2	7.3	1.5	-2.9	1.3	0.8	-0.9
Romania	6.2	-9.3	15.5	0	-6.5	-0.2	-1.2	-1.4
Denmark	5.8	-2	7.8	-0.6	-3.6	1.9	-0.3	0.6
Lithuania	5.2	-1.6	6.8	0.8	-4.1	-1	2	0.7
Malta	2.1	3.5	-1.4	0	-1.4	1.4	0.2	3.3
Spain	1.3	-2.9	4.2	0.4	-5.4	1	0.5	0.6
Slovenia	-3.4	-9.3	5.9	0.1	-8.5	0.5	0.3	-1.7

Table A2: RIF Quantile Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	.10	.20	.30	.40	.50	.60	.70	.80	.90
Benefits and pay	0.028***	0.023***	0.019***	0.020***	0.017***	0.020***	0.019***	0.020***	0.019***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Close to home	-0.017***	-0.015***	-0.018***	-0.020***	-0.016***	-0.015***	-0.016***	-0.014***	-0.013***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Security	0.001	-0.004	-0.004	-0.005*	-0.007***	-0.009***	-0.012***	-0.018***	-0.020***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Suits skills	0.023***	0.017***	0.010***	0.008***	0.008***	0.010***	0.009***	0.006***	0.004
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Gain experience	-0.003	-0.006***	-0.008***	-0.013***	-0.010***	-0.010***	-0.009***	-0.006***	-0.008***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Career progression	0.017***	0.010***	0.015***	0.021***	0.015***	0.014***	0.012***	0.012***	0.017***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Reputation of firm	0.002	-0.001	-0.001	-0.002	0.002	0.002	0.003	0.002	-0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Likes the work	-0.007	0.004	0.006**	0.012***	0.008***	0.006**	0.004**	0.006***	0.006*
	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Work-life balance	0.006	0.004	0.007***	0.008***	0.004*	0.002	0.001	0.002	0.001
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Male	0.212***	0.173***	0.153***	0.131***	0.087***	0.089***	0.109***	0.127***	0.133***
	(0.016)	(0.011)	(0.011)	(0.012)	(0.009)	(0.009)	(0.008)	(0.009)	(0.012)
Age	0.040***	0.045***	0.046***	0.045***	0.033***	0.031***	0.028***	0.023***	0.016***
	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)
Agesq	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Medium education	0.180***	0.166***	0.192***	0.234***	0.229***	0.211***	0.156***	0.112***	0.130***
	(0.027)	(0.019)	(0.018)	(0.021)	(0.016)	(0.015)	(0.013)	(0.014)	(0.017)
High education	0.506***	0.423***	0.458***	0.532***	0.440***	0.438***	0.395***	0.382***	0.416***
	(0.026)	(0.018)	(0.018)	(0.021)	(0.016)	(0.015)	(0.014)	(0.015)	(0.019)

Job tenure	0.014***	0.011***	0.011***	0.011***	0.010***	0.010***	0.009***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Private sector	-0.006	-0.003	-0.029***	-0.039***	-0.015	0.013	0.032***	0.058***	0.072***
	(0.016)	(0.011)	(0.011)	(0.012)	(0.010)	(0.009)	(0.009)	(0.010)	(0.013)
Prev employed	0.133**	0.120***	0.099***	0.086***	0.122***	0.068***	0.047**	0.032	0.039
	(0.052)	(0.033)	(0.031)	(0.033)	(0.026)	(0.024)	(0.022)	(0.024)	(0.029)
Prev self employed	0.101	0.065	0.087**	0.095**	0.117***	0.078**	0.064**	0.067**	0.019
	(0.066)	(0.044)	(0.042)	(0.045)	(0.035)	(0.032)	(0.030)	(0.033)	(0.041)
Prev education	0.077	0.081**	0.066**	0.081**	0.116***	0.069***	0.034	0.004	0.010
	(0.053)	(0.035)	(0.033)	(0.035)	(0.027)	(0.025)	(0.024)	(0.026)	(0.032)
Prev unemployed	-0.098*	-0.039	-0.055*	-0.098***	-0.025	-0.046*	-0.057**	-0.059**	-0.022
	(0.057)	(0.036)	(0.033)	(0.036)	(0.028)	(0.026)	(0.024)	(0.026)	(0.032)
Constant	-0.200	0.309***	0.889***	1.257***	1.723***	1.998***	2.325***	2.334***	2.691***
	(0.168)	(0.115)	(0.109)	(0.127)	(0.095)	(0.092)	(0.089)	(0.100)	(0.133)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,181	29,181	29,181	29,181	29,181	29,181	29,181	29,181	29,181
R-squared	0.355	0.467	0.564	0.612	0.576	0.507	0.422	0.318	0.200

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The coefficients represent the marginal effect on the unconditional wage decile.

Table A3: Percentage difference in average motives of men and women across wage percentiles

Wage percentile	Suits skills	Experience	Security	Career	Reputation	Benefits	Close to home	Like the work	Work-life
0-10	-2.4	-5.7	-6.7	1.8	-2.2	2.4	-6.2	-2.8	-7.1
10-20	0.5	-3.6	-5.8	1.8	-0.4	4.7	-2.7	-2.2	-5.7
20-30	-2.6	-6.8	-8.3	-2.7	-2.2	1.7	-5.2	-3.2	-5.0
30-40	-3.8	-5.9	-5.3	-0.1	-1.2	0.0	-4.2	-1.5	-5.3
40-50	-4.4	-6.1	-4.7	-1.7	1.2	3.8	-2.2	-2.5	-2.2
50-60	-3.7	-5.7	-3.0	0.5	1.6	5.1	-2.5	-2.6	-3.6
60-70	-4.2	-6.4	-3.7	2.0	0.5	2.9	-3.9	-3.3	-3.5
70-80	-5.7	-5.7	-3.3	0.5	0.4	4.3	-2.2	-3.8	-4.3
80-90	-4.8	-8.2	-3.5	-0.6	0.6	2.8	-6.5	-4.1	-2.2
90-100	-1.2	-4.9	-4.2	0.4	0.4	5.0	-3.2	-1.4	-1.7

Note: A positive number means the average for males is higher than females.

Table A4: Decile Decomposition

	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9
Raw differential	18.6	13.7	12.2	16.7	9.8	10.1	10.3	13.2	15.2
Explained (p.p.)	-1.3	-1.2	-1.3	-0.5	-0.1	0.1	0.2	0.6	1.2
Unexplained (p.p.)	19.9	14.9	13.5	17.2	9.9	10	10.1	12.6	14
Category	Explained (p.p.)	Explained (p.p.)	Explained (p.p.)	Explained (p.p.)	Explained (p.p.)	Explained (p.p.)	Explained (p.p.)	Explained (p.p.)	Explained (p.p.)
Age	-0.3	-0.1	0.2	0.4	0.4	0.5	0.6	0.8	1
Education	-3.7	-3	-3.5	-3.4	-3.1	-3.5	-3.5	-3.4	-3.5
Job-related	1	0.9	0.5	0.7	1.1	1.6	1.5	1.5	1.6
Prev employment status	1	-0.0	0.3	0.6	0.3	0.1	0.2	0.2	0.2
Job motives	0.8	1.1	1.1	1.3	1.1	1.4	1.5	1.6	1.8
Motives									
Suits skills	-0.45	-0.27	-0.17	-0.17	-0.22	-0.28	-0.26	-0.18	-0.20
Gain experience	0.10	0.29	0.43	0.57	0.40	0.45	0.47	0.42	0.42
Job security	0.18	0.32	0.06	0.32	0.28	0.40	0.58	0.80	1.03
Career progression	0.01	0.01	0.02	0.03	0.02	0.02	0.02	0.02	0.02
Reputation of firm	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Benefits and pay	0.67	0.56	0.48	0.43	0.44	0.50	0.47	0.45	0.45
Close to home	0.35	0.42	0.49	0.48	0.40	0.45	0.40	0.40	0.35
Likes the work	0.03	-0.13	-0.12	-0.21	-0.09	-0.05	-0.11	-0.20	-0.20
Work-life balance	-0.13	-0.13	-0.09	-0.20	-0.10	-0.09	-0.09	-0.11	-0.05
Total (p.p.)	**0.76**	**1.07**	**1.10**	**1.25**	**1.13**	**1.40**	**1.48**	**1.61**	**1.81**
As % of raw diff	**4.15 %**	**7.81 %**	**9.02 %**	**7.49 %**	**11.53 %**	**13.86 %**	**14.37 %**	**12.20 %**	**11.91 %**