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ORIGINAL PAPER

About time: the narrowing gender wage gap in Austria

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Abstract

We examine the gender wage gap in Austria from 2005 to 2017 using data from EU-SILC. The raw gap of hourly wages declined from 18.6 log points in 2005 to 14.9 log points in 2017. We use standard decomposition techniques that correct for differences in the distributions of human capital and other variables between men and women. Decompositions of the wage gap indicate that both the explained and the unexplained part of the gender wage gap decreased substantially over the last ten years. Using the approach developed by Neumark (J Hum Resour 22:279–295, 1988), the unexplained wage gap shrank from 8.7 log points in 2005 to 5.1 log points in 2017. The main reason for the decline in wage differences was the relative improvement of women's observed and unobserved characteristics.

Keywords Gender wage differentials · Wage inequality · Decomposition · EU-SILC

JEL Classification J31 · J71

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1 Introduction

Goldin (2014) demonstrated that the US gender wage gap is much smaller than it had once been and she concludes that this decline is the result of increases in the human capital of women relative to men. In contrast, Blau and Kahn (2017), using PSID data for 1980–2010, stress that because US women exceed men in educational attainment by now, traditional human capital factors, although they were essential for the narrowing of the gender wage gap, explain little of the still existing wage gap. In addition, the unexplained component of the US gender wage gap did not fall much between the 1990s and 2010. They conclude that differences in the selection into occupations and industries are the most important aspect of the persistent US gender wage gap.

Böheim et al. (2013) summarize several studies of the gender wage gap in Austria and conclude that the gender wage gap hardly changed during the 1990s and that it decreased between 2002 and 2007 (Böheim et al. 2007, 2013). However, there is no study for Austria that uses a consistent source of data to analyze such development over a longer time. Earlier work used different data or different empirical methods. See, for example, Zweimüller and Winter-Ebmer (1994), Pointner and Stiglbauer (2010), Bundesministerium (2010), Grandner and Gstach (2015) or Christl and Köppl-Turyna (2020). This makes an assessment of the gender wage gap's evolution over time difficult.

We provide an analysis of the development of the gender wage gap in Austria for the period 2005–2017, using data from the Austrian EU-SILC (Austria 2018). The EU-SILC is the only long-term yearly survey which is currently available for Austria. It provides a range of personal characteristics and job-specific information which allows us to contrast changes over time, using a unified and consistent approach. In our sample of employees from the private and public sector, the wage gap without controlling for any differences between men and women declined from 18.6 (20.7) log points in 2005 (2006) to 15.0 log points in 2017. For employees in the private sector, this raw gap declined from 21.6 (23.6) in 2005 (2006) to 13.5 in 2017.

We expect to find a narrowing of the gender wage gap over this period for several reasons. First, women became more attached to the labor market over the last decades. Women's labor force participation rate in Austria in 2005 was 51.3% and it was 55.9% in 2017 (OECD 2019). In contrast, men's participation rates were 66.4% in 2005 and 66.8% in 2017. Second, women's educational attainment increased over time (Statistik 2019a). In 2000, 84.9% of women who were between 20 and 24 years of age had at least upper secondary level education; among men, it was 85.3%. By 2017, 90.2% of women and 84.7% of men aged 20–24 years of age had at least upper secondary education. Thirdly, the gender wage gap regularly features in political debates and several attempts have been made to address unfair wage discrimination by gender. For example, since 2014, banks have been required to formulate a quota

for the board of directors and the executive directors to improve the representation of underrepresented employees (Wieser and Fischeneder 2019).

However, there are also reasons to expect little change in the gender wage gap over time. Although women's labor market participation increased, much of this increase is due to an increase in part-time work. In 2005, women's part-time rate was 40.4% and it was 48.3% in 2017. In contrast, men's part-time rate increased from 5.7% in 2005 to 11.0% in 2017. In terms of education, women and men tend to choose different fields and there has been little change over the years. For example, in the winter term of 2005, 10.3% of all male students and 7.9% of all female students enrolled in Science, Technology, Engineering, and Mathematics (STEM) studies.[1] In 2017, these numbers were 14.1% and 11.5%. In 2005, the most popular profession for female apprentices was sales (24.9%) and it was automotive engineering for male apprentices (8.6%).[2] In 2017, 23.5% of female apprentices trained in sales, which was still the most popular profession among women (Wirtschaftskammer 2018). Among men, automotive engineering was only the third most popular choice (9.5%) and metal engineering was the most popular (13.7%). While there have been political initiatives and legal reforms to reduce the gender wage gap and gender equality, for example, gender quotas for the board of directors in large companies, most of these seem to mainly raise awareness as they do not involve penalties or fines.

We decompose the gender wage gap into an explained and into an unexplained part, using several standard decomposition methods (Blinder 1973; Oaxaca 1973; Neumark 1988; Reimers 1983; Cotton 1988; Juhn et al. 1991; Oaxaca and Ransom 1995) to analyze which characteristics are associated with the evolution of the gender wage gap over time. In this way, our results contribute to the public debate which usually focuses on the question of how much of this difference is based on differences in characteristics, and how much is not based on such differences, perhaps due to unfair treatment of women. (Unequal treatment either due to prevailing gender stereotypes or limited access, e.g., to certain educational tracks or occupations, can, of course, result in observed differences.) A part of the gender wage gap might be due to other factors not included in our analyses, e.g., proficiency in skills, as these data do not provide such information.

Our results allow an assessment if and how women's improved human capital, such as educational attainment and labor market experience, contribute to a closing of the gender wage gap. The main determinant of the decline in both the private and the public sector is the relative improvement of the women's observed and unobserved characteristics. Using the decomposition method by Neumark (1988), we find that, after controlling for human capital, occupation, and other explanatory variables, the gap in a sample of both public and private sector employees shrank from 8.7 (8.8) log points in 2005 (2006) to 5.07 log points in 2017. Analyzing

[1] The rates are for Austrian nationals only; there were 110,363 male and 123,828 female students in 2005, and 116,412 male and 127,459 female students in 2017 (Statistik Austria 2019c).

[2] In 2005, 74.2% of all female apprentices trained in the 10 most frequently chosen professions; among men, only 48% trained in the 10 most popular professions (Wirtschaftskammer 2006).

only private sector employees, the unexplained gap declined from 9.9 (9.5) in 2005 (2006) to 5.06 log points in 2017. All our decompositions indicate that the unexplained part of the gender wage gap decreased substantially over the last ten years. The decrease of the unexplained gender wage gap between the largest gap in this period (2006) and the most recent gap (2017) ranges from 3.7 log points to 8.5 log points depending on the decomposition approach.

2 Data

We use data from the Austrian European Union Statistics on Income and Living Conditions (EU-SILC) covering the years 2005–2017 (Austria 2018). EU-SILC is an annual survey of about 6000 households with about 14,000 persons. The survey is a combined cross-sectional and longitudinal survey where each year about a quarter of observations are dropped from the survey, while a similar number of observations is added. Each quarter of the sample remains in the survey for four years. The survey collects data on income, poverty, social exclusion, housing, labor, education, and health at the household and individual levels.

Our empirical analysis uses wage regressions that also control for sample selection using a Heckman procedure (Heckman 1979). We include persons who are between 20 to 60 years of age and analyze the wages in their main job. Our main sample consists of both private and public sector employees. We repeat some of our analyses also for the private sector separately and show the results in the Appendices 1 (tables) and 2 (figures). EU-SILC does not provide an hourly wage. We calculate the hourly gross wage by dividing the usual monthly earnings (including overtime and bonuses) by the number of usual hours in paid work. We deflate all wage data to prices of 2014 using the Consumer Price Index (CPI) (Statistik Austria 2019b). Men and women might self-select into the labor market and in order to correct our estimates for sample selection, we add non-working persons to our sample.

Table 1 shows the average real gross hourly wages for men and women, 2005–2017. During this period, average wages increased moderately. Men's average wages were Euro 15.35 in 2005 and Euro 16.06 in 2017. Women's average wages increased from Euro 13.02 in 2005 to Euro 13.76 in 2017.[3] Men's average hours fluctuated moderately at around 41 h/week over the period. Women worked on average about 20% fewer hours per week than men, their hours fluctuated around 33 h/week.[4]

[3] Figure 4 in Appendix 2 shows the implied distribution of log hourly earnings by gender in 2007, 2009, 2011, 2013, 2015, and 2017. In all years, we observe that the distribution of women's wages was to the left of the distribution of men's wages. This indicates that women's wages were on average lower than men's wages. We also observe that the gap between female and male wages was rather constant over the wage distribution.

[4] In the private sector, men's average wages were Euro 14.96 in 2005 and Euro 15.74 in 2017. Women's average wages increased from Euro 12.17 in 2005 to Euro 13.16 in 2017. See Table 10 in Appendix 1. Men worked about 41 h per week, women about 33 h.

Table 1 Average wages and usual weekly hours, 2005–2017, by gender

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Men													
Wage	15.35	15.50	15.60	15.23	16.24	16.40	16.21	16.14	16.11	16.30	16.27	16.50	16.06
Hours	41.04	40.64	42.01	42.19	41.74	41.33	40.95	41.26	41.32	40.47	40.79	40.85	41.96
Obs.	2390	2691	2991	2359	2303	2499	2445	2263	2280	2277	2276	2304	2308
Women													
Wage	13.02	12.77	12.78	12.61	13.81	13.88	13.63	13.41	13.37	13.76	13.82	14.11	13.76
Hours	33.19	33.48	32.85	33.47	33.08	33.25	33.07	32.63	33.13	32.27	32.30	32.48	32.55
Obs.	1942	2255	2567	2067	2094	2295	2315	2227	2148	2166	2218	2217	2344

Austrian EU-SILC data 2005–2017 (Austria 2018). Gross hourly wages in Euros, deflated using the CPI (base year is 2014)

We use a range of variables which describe personal characteristics, household characteristics, and job-related characteristics. The summary statistics of all these variables are tabulated in Tables 11 (personal and household characteristics) and 12 (job characteristics) in Appendix 1 for the years 2007, 2009, 2011, 2013, 2015, and 2017. The variables are typical indicators that are thought to proxy the productivity of employees and firms, and thus should be relevant in the determination of wages. These are age, education, experience, health status, household size, nationality, occupation, contract type, sector, position in the firm, region, and firm size.[5]

3 Empirical methods

In our empirical analyzes, we examine how wage differences between men and women in Austria have evolved over time. We first analyze the wage gap for each year from 2005 until 2017 using Blinder–Oacaxa-type decompositions (Blinder 1973; Oaxaca 1973; Neumark 1988; Reimers 1983; Cotton 1988; Oaxaca and Ransom 1995). The descriptive analysis shows an increase in the wage differential at the beginning of our observation period and a decrease towards the end of the period. As we are particularly interested in which variables contribute to the observed changes, we analyze in a second step the change in the wage gap between 2006, when the gender wage gap was the greatest in this period, and 2017, the latest available data, using Juhn–Murphy–Pierce decomposition techniques (Juhn et al. 1991).

We decompose the differences in the mean wages of women and men based on the technique first developed by Blinder (1973) and Oaxaca (1973). We estimate wage equations separately for women (W) and men (M) with ordinary least squares,

$$\ln y_{ig} = \beta_g X_{ig} + \epsilon_{ig}, \tag{1}$$

where y_{ig} is the hourly wage of employee i, $i = 1, \ldots, N$, of gender g, $g = M, W$; β_g are the coefficients to be estimated; X_{ig} is a vector of characteristics; and ϵ_{ig} is an i.i.d. error. Besides indicators for human capital, family structure, occupation, and firm characteristics, we also include a Heckman selection term in X_{ig} to account for different probabilities of working (Heckman 1979). In the participation equation, we use as identifying variables the number of children between 0 and 2, between 3 and 5, between 6 and 9, as well as those between 10 and 18. We also use the health status of the partner as an exclusion restriction. The underlying assumption is that children and chronically sick partners constrain the possibility for paid work, but do not impact on the wage itself. (This assumption might be violated if, for example, persons with children have lower bargaining power over wages.)

The difference in the mean wages, Y_g, can be decomposed (Oaxaca and Ransom 1995):

[5] One might worry that the large number of explanatory variables could lead to sparsity in the estimated wage regressions, i.e., a coefficient vector that contains many zeros (Hastie et al. 2009). However, as Böheim and Philipp (2020) show there is very little difference between wage decompositions that are based on OLS and those that use LASSO for variable selection.

$$Y_M - Y_W = \hat{\beta}^*(\overline{X}_M - \overline{X}_W) + (\hat{\beta}_M - \hat{\beta}^*)\overline{X}_M + (\hat{\beta}^* - \hat{\beta}_W)\overline{X}_W, \quad (2)$$

where $\hat{\beta}^*$ is a weighted average of the coefficient vectors, i.e., $\hat{\beta}^* = \Omega\hat{\beta}_M + (I - \Omega)\hat{\beta}_W$, with a weighting matrix Ω and the identity matrix I. The first term on the right-hand side of Eq. (2) is the difference between men and women in their mean characteristics, evaluated at $\hat{\beta}^*$. It is that part of the wage gap that is due to observable differences, for example, proxies for productivity such as educational attainment. The sum of the second and the third term is the part of the wage gap which cannot be ascribed to observed differences. We calculate the decomposition separately for each year in our sample.

The decompositions proposed by Blinder (1973) and Oaxaca (1973) represent special cases of Eq. (2), where Ω is either equal to I or the null-matrix. In the first case, Eq. (2) corresponds to the "male-based" decomposition which assumes that men are paid their marginal product and women are negatively discriminated against. In contrast, when Ω is the null-matrix, a "female-based" view assumes that women are paid their marginal product and men are positively discriminated against. We first follow Neumark (1988) and estimate a pooled model to derive the counterfactual coefficient vector $\hat{\beta}^*$. We then also apply Reimers (1983) who assumes $\hat{\beta}^* = (1/2)\hat{\beta}_M + (1/2)\hat{\beta}_W$. Finally, because the number of men, n_M, and the number of women, n_W, differ in our sample, we use Cotton (1988) who weights the coefficients by the group sizes, n_M and n_W, i.e., $\hat{\beta}^* = [n_M/(n_M + n_W)]\hat{\beta}_M + [n_W/(n_M + n_W)]\hat{\beta}_F$.

For the second part of our analysis, we decompose the differences in the gender wage gap over time into a portion due to gender-specific factors and a portion due to differences in the overall level of wage inequality (Juhn et al. 1991).[6] Suppose that wages for employee i of gender g in period t is given by the following equation:

$$\ln y_{igt} = \beta_{gt}X_{igt} + \sigma_{gt}\theta_{igt}, \quad (3)$$

where y_{igt} are gross hourly wages, X_{igt} is a vector of explanatory variables including a Heckman selection term, β_{gt} is a vector of explanatory coefficients, θ_{igt} is a standardized residual (i.e., with mean zero and a variance of one for each point in time), and σ_{gt} is the period's residual standard deviation of wages (i.e., the unexplained level of wage inequality among men).

The difference in the average wages of men and women at time t is given by:

$$D_t = Y_{Mt} - Y_{Wt} = \beta_t(X_{Mt} - X_{Wt}) + \sigma_t(\theta_{mt} - \theta_{ft}) = \beta_t\Delta X_t + \sigma_t\Delta\theta_t, \quad (4)$$

where Y_{gt} refers to average wages of men and women at time t, and Δ is the difference operator. A change in the difference between two periods t and s can be decomposed as:

[6] Our presentation follows Blau and Kahn (1992), Jann (2008), and Böheim et al. (2013). For a more general discussion of this method see Fortin et al. (2011).

$$D_t - D_s = \beta_s(\Delta X_t - \Delta X_s) + (\beta_t - \beta_s)\Delta X_s + (\beta_t - \beta_s)(\Delta X_t - \Delta X_s) + \sigma_s(\Delta\theta_t - \Delta\theta_s) + (\sigma_t - \sigma_s)\Delta\theta_s + (\sigma_t - \sigma_s)(\Delta\theta_t - \Delta\theta_s). \quad (5)$$

The first term on the right-hand side measures the change in the differences in observed characteristics X between men and women over time. It describes how differences between men and women in, for example, educational attainment or experience have changed over time. The second term measures how the differences in the observed returns to education or experience have changed over time. A negative change can be interpreted as a reduction in differences in returns to education. The third term adjusts for simultaneous changes in quantities and prices. The fourth term measures the effect of differences in the relative residual wage position of men and women over time, i.e., the relative ranking of women within the male residual wage distribution. Such differences in rankings may reflect gender differences in unmeasured characteristics or the impact of labor market discrimination against women. Unmeasured characteristics could be negotiation outcomes (Artz et al. 2018) or personality traits as the propensity to compete. Research by, for example, Niederle and Vesterlund (2007) has shown that women shy away from competition and men compete too much. With this term we may measure how differences in these characteristics change over time. Again, a negative term may indicate that women have caught up in these characteristics over time. The fifth term measures the part of the wage gap that is due to changes in residual inequality, i.e., how changes in unobserved prices for the unobserved quantities affect the change in the wage gap. This term assesses the changing prices, for example, for the propensity to compete or that the amount of discrimination has changed over time. The last term again adjusts for simultaneous changes in unobserved quantities and unobserved prices.

4 Decomposition results

We start with a presentation of the results of several Blinder–Oaxaca-type decompositions for each year from 2005 until 2017. The raw gender wage gap increased between 2005 and 2006, where it reached a peak in the years of observation. After 2006, the gender wage gap fluctuated around a downward trend. We, therefore, choose 2006 and 2017 as the reference years for our further analyses. In particular, we calculate decompositions for these years adding sets of explanatory variables to the regression model sequentially. We show these results in Sect. 4.2. Then, in Sect. 4.3, we show which variables contributed to the changes in the gap between 2006 and 2017. Finally, in Sect. 4.4, we present the results of Juhn–Murphy–Pierce decompositions for 2006 and 2017 to assess the contribution of variables and prices to the change in the raw gender wage gap.[7]

[7] Our decompositions are based on regression models which include a Heckman correction. We show the estimation results for the years 2007, 2009, 2011, 2013, 2015, and 2017 in Table 13 and the results of the participation equations in Table 14 in Appendix 1.

Table 2 Gender wage decompositions, 2005–2017

Year	Wage gap	Difference over time	Explained gap	Difference over time	Unexplained gap	Difference over time
2005	0.1862		0.0988		0.0874	
2006	0.2071	0.0210	0.1190	0.0202	0.0881	0.0008
2007	0.2040	− 0.0031	0.1154	− 0.0036	0.0887	0.0005
2008	0.1941	− 0.0099	0.1109	− 0.0045	0.0832	− 0.0054
2009	0.1711	− 0.0230	0.1002	− 0.0107	0.0709	− 0.0124
2010	0.1605	− 0.0106	0.0925	− 0.0077	0.0679	− 0.0029
2011	0.1654	0.0050	0.0999	0.0073	0.0656	− 0.0024
2012	0.1874	0.0220	0.1069	0.0070	0.0806	0.0150
2013	0.1870	− 0.0005	0.1150	0.0081	0.0720	− 0.0086
2014	0.1716	− 0.0154	0.1003	− 0.0147	0.0713	− 0.0007
2015	0.1624	− 0.0092	0.0921	− 0.0081	0.0702	− 0.0010
2016	0.1574	− 0.0050	0.0959	0.0038	0.0615	− 0.0088
2017	0.1489	− 0.0085	0.0982	0.0023	0.0507	− 0.0108
2006	0.2071		0.1190		0.0881	
2017	0.1489	− 0.0582	0.0982	− 0.0207	0.0507	− 0.0375

Results from Blinder-Oaxaca decompositions. Dependent variable is the logarithm of hourly gross wages. Explanatory variables used in all decompositions are age, education, experience, health status, household size, nationality, occupation, contract type, sector, position in the firm, region, firm size, and a correction (inverse Mill's ratio) to adjust for non-random selection into employment

Table 3 Comparison of decompositions from 2005 until 2017

Year	Wage difference	Unexplained gap				
		Neumark	Female dummy	Reimers	Cotton	Male based
2005	0.1862	0.0874	0.1430	0.1524	0.1544	0.1332
2006	0.2071	0.0881	0.1458	0.1524	0.1540	0.1350
2007	0.2040	0.0887	0.1477	0.1557	0.1573	0.1348
2008	0.1941	0.0832	0.1358	0.1521	0.1535	0.1306
2009	0.1711	0.0709	0.1181	0.1373	0.1397	0.0862
2010	0.1605	0.0679	0.1112	0.1223	0.1229	0.1090
2011	0.1654	0.0656	0.1040	0.1071	0.1079	0.0761
2012	0.1874	0.0806	0.1329	0.1450	0.1452	0.1183
2013	0.1870	0.0720	0.1201	0.1149	0.1158	0.0837
2014	0.1716	0.0713	0.1199	0.1217	0.1226	0.0873
2015	0.1624	0.0702	0.1193	0.1320	0.1324	0.1034
2016	0.1574	0.0615	0.1018	0.1022	0.1026	0.0852
2017	0.1489	0.0507	0.0820	0.0903	0.0904	0.0499
2006	0.2071	0.0881	0.1458	0.1524	0.1540	0.1350
2017	0.1489	0.0507	0.0820	0.0903	0.0904	0.0499

Results from various decompositions. Dependent variable is the logarithm of hourly gross wages. Explanatory variables used in all decompositions are age, education, experience, health status, household size, nationality, occupation, contract type, sector, position in the firm, region, firm size, and a correction (inverse Mill's ratio) to adjust for non-random selection into employment

4.1 Results of Blinder–Oaxaca decomposition for all years

In Table 2, we present the results from decompositions of the gender wage gap for the years 2005 until 2017. In each year, we use the year's pooled sample as the reference distribution (Neumark 1988). In 2005, the average gender wage gap was 18.62 log points, which increased to 20.71 log points in 2006. This is a difference of about 2.1 log points. After 2006, the gender wage gap shrank over time, fluctuating around a downward trend. It was 16.05 log points in 2010, 18.74 log points in 2012, 17.16 log points in 2014, and it was 14.89 in 2017. From 2006 until 2017, the change amounted to 5.8 log points.

The decomposition results indicate that over the whole period the unexplained gender wage gap decreased as well. In 2005, the differences in observed characteristics explained 9.88 log points of the total gap, or 53%, the unexplained part was 8.74 log points. The unexplained part was 8.81 log points (42%) in 2006 and 5.07 log points (34%) in 2017. From 2006 until 2017, the unexplained part of the wage gap declined by 3.75 log points.

These results indicate that the reduction in the raw gender wage gap was driven by a change in the explained and the unexplained gap. Both a reduction in the difference between men's and women's observable characteristics as well as in unobservable characteristics contributed to a lower gap over time. In Appendix 1 in Table 15, we also present results of a Blinder–Oaxaca decomposition where we use

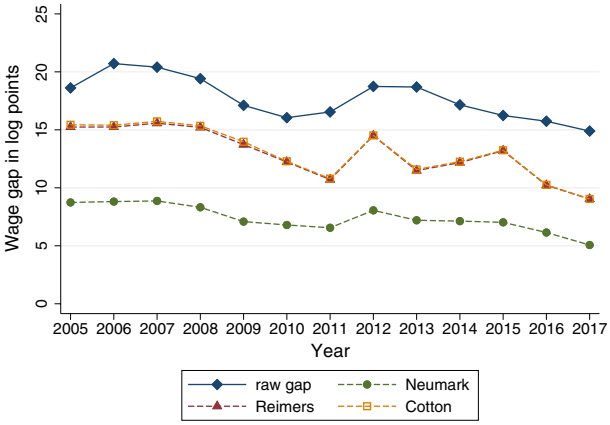

Fig. 1 Gender wage gap in Austria, 2005–2017. *Notes*: Austrian EU-SILC data 2005–2017 (Austria 2018). Raw gap and residuals from different decomposition methods. Explanatory variables used in all decompositions are age, education, experience, health status, household size, nationality, occupation, contract type, sector, position in the firm, region, firm size, and a correction (inverse Mill's ratio) to adjust for non-random selection into employment

only observations of private sector employees. We observe the same pattern as in the overall sample. The raw gender wage gap was, however, wider than in the overall sample and declined more pronouncedly.

To assess the robustness of these results, we also calculated the explained and unexplained gap from several other decomposition approaches. In Table 3, we present results from a male-based decomposition (Blinder 1973; Oaxaca 1973), from a coefficient weighting scheme as proposed by Reimers (1983) and Cotton (1988), and from a decomposition that uses a pooled regression with a group dummy variable. The decrease of the unexplained gender wage gap between 2006 and 2017 ranges from 3.7 log points to 8.5 log points depending on the decomposition approach. While the true counterfactual wage distribution is unknown, all calculated decompositions indicate that the unexplained part of the gender wage gap decreased substantially over the last ten years.

Figure 1 is a graphical representation of Table 3 for selected decompositions. We observe a declining gender wage gap both with and without controlling for differences in characteristics, such as education, experience, occupation, industry, degree of urbanization, firm size, and hierarchy level.[8]

4.2 Results of step-wise Blinder–Oaxaca decomposition for 2006 and 2017

To illustrate the effect of human capital variables such as education and experience in comparison to occupation, industry, hierarchy, and other explanatory variables,

[8] When we restrict our sample to private sector employees, we observe a similar pattern. See Fig. 5 in Appendix 2.

Table 4 Decomposition of wage differentials, 2006 and 2017

Estimated value	(1)	(2)	(3)	(4)	(5)
2006 Neumark (1988)	0.2071	0.1784	0.1208	0.1039	0.0881
In % of the mean wage differential	100.0	86.1	58.3	50.1	42.6
2006 Reimers (1983)	0.2071	0.2030	0.1598	0.1736	0.1524
In % of the mean wage differential	100.0	98.0	77.2	83.8	73.6
2017 Neumark (1988)	0.1489	0.1438	0.0934	0.0626	0.0507
In % of the mean wage differential	100.0	96.5	62.7	42.0	34.0
2017 Reimers (1983)	0.1489	0.1539	0.1187	0.1093	0.0903
In % of the mean wage differential	100.0	103.4	79.7	73.4	60.6
Education		×	×	×	×
Experience, marital status, part-time			×	×	×
Status, occupation, industry, region, citizenship				×	×
Firm size, hierarchy					×

Results from Blinder–Oaxaca-type decompositions. The dependent variable is the logarithm of hourly gross wages. Explanatory variables used in all decompositions are age, education, experience, health status, household size, nationality, occupation, contract type, sector, position in the firm, region, firm size, and a correction (inverse Mill's ratio) to adjust for non-random selection into employment

we estimate Blinder–Oacaxa-type decompositions and add groups of explanatory variables sequentially. We start with a specification that only includes indicators for formal educational attainment. In a next step, we add variables related to experience, followed by occupation, status, and degree of urbanization. Finally, we add firm size and position in the corporate hierarchy. We present the results for 2006 and 2017 in Table 4.

In 2006, the raw wage gap was 20.71 log points. Using Neumark's (1988) approach, about 14% of this difference is attributed to the different educational attainments that men and women have in our sample. The in this way corrected gap is about 17.84 log points, i.e., 86.1% of the wage gap cannot be explained by differences in educational background. Observed characteristics which are related to labor market experience (experience, marital status, and part-time work) reduce the gap further to about 12.08 log points, or 58.3% of the raw gap. This shows that the difference in men's and women's labor market experience explains a substantial part of the gender wage gap. Additional characteristics such as status, occupation, industry, degree of urbanization, and country of origin reduce the gap to 10.39 log points, or to about half of the raw gap. Accounting for differences in the size of firms and the hierarchy levels of men and women reduce the gap to 8.81 log points, which leaves 42.5% of the gender wag gap unexplained.

Comparing these numbers with those from 2017 shows that in 2017 differences between men and women in education contributed less to explaining the gender wage gap. This indicates that men and women differed less in their education in

Table 5 Detailed decomposition of wage differentials in 2006 and 2017

	2006		2017	
	Coef.	SE	Coef.	SE
Explained				
Sum	0.1190	0.0004	0.0982	0.0004
Origin*	− 0.0007	0.0000	0.0004	0.0000
Urbanization*	− 0.0007	0.0000	− 0.0001	0.0000
Education*	− 0.0069	0.0002	− 0.0117	0.0001
Experience*	0.0308	0.0001	0.0154	0.0001
Occupation*	0.0323	0.0002	0.0281	0.0002
Industry*	0.0105	0.0002	0.0421	0.0002
Hierarchy*	0.0218	0.0001	0.0209	0.0001
Occ. status*	− 0.0100	0.0001	− 0.0182	0.0001
Cohabiting partner	0.0004	0.0000	− 0.0005	0.0000
Firm size ≥ 10	0.0109	0.0001	0.0113	0.0001
Part− time	0.0175	0.0002	0.0092	0.0002
Mills ratio	0.0131	0.0002	0.0014	0.0001
Unexplained				
Sum	0.0881	0.0003	0.0507	0.0003
Origin*	0.0432	0.0010	0.0440	0.0008
Urbanization*	0.0209	0.0005	0.0034	0.0005
Education*	− 0.0533	0.0011	0.0119	0.0011
Experience*	− 0.0025	0.0013	0.0301	0.0011
Occupation*	− 0.0190	0.0008	− 0.0338	0.0008
Industry*	− 0.0449	0.0011	− 0.0195	0.0010
Hierarchy*	− 0.0026	0.0003	− 0.0120	0.0003
Occ. status*	− 0.0028	0.0004	− 0.0049	0.0003
Cohabiting partner	0.0639	0.0006	0.0016	0.0005
Firm size ≥ 10	0.0223	0.0007	− 0.0134	0.0006
Part-time	− 0.0265	0.0002	− 0.0277	0.0002
Mills ratio	− 0.0123	0.0005	− 0.0050	0.0004
Constant	0.1017	0.0027	0.0760	0.0025
Observations	4946		4628	
Observations men	2691		2308	
Observations women	2255		2320	

Results from Blinder–Oaxaca decompositions. The dependent variable is the logarithm of hourly gross wages. Explanatory variables used in all decompositions are age, education, experience, health status, household size, nationality, occupation, contract type, sector, position in the firm, region, firm size, and a correction (inverse Mill's ratio) to adjust for non-random selection into employment.

*Indicates overall effects for sets of binary indicators

2017 than in 2006. The gender gap in 2017 was 14.89 and differences in education explain about 3.4% of the overall wage gap. In other words, accounting for differences in formal education between men and women leaves 96.6% of the wage gap unexplained. However, differences in labor market experience are related to differences in wages. The wage gap after accounting for differences in education and experience is 9.34 log points, which leaves 62.7% of the gap unexplained.[9] Accounting for differences in status, occupation, industry, degree of urbanization, and country of origin reduces the gap to 6.26 log points (42%).[10] Accounting for different firm sizes and hierarchy levels lowers the unexplained gap to 5.07 log points (34%).[11]

In Table 4, we also show the results using the approach by Reimers (1983). We observe a similar pattern. However, the share of the unexplained part is larger than for the decomposition by Neumark (1988).

4.3 Detailed Blinder–Oaxaca decomposition for 2006 and 2017

In Table 5, we show detailed decomposition results for the years 2006 and 2017 and the contributions to the explained and the unexplained part. On average, men and women became more similar in many observed characteristics which is illustrated by the estimated coefficients tabulated in the first panel ("explained") of Table 5. Women acquired notably more labor market experience over time and, on average, became more similar to men in this respect. This can be seen in the estimated explained contribution to the gender wage, which in 2006 was about 3.1 log points. This estimate implies that one part of the gender wage gap in 2006 was due to women having less labor market experience than men. By 2017, this difference had become smaller and differences in labor market experience were responsible for about 1.5 log points of the average gender wage gap. Industrial segregation, however, deepened over time and observed differences between men and women led to greater differences in wages than before.

In the second panel of Table 5, we detail the contributions to the unexplained part of the gender wage gap. A positive (negative) unexplained contribution factor implies that for similar women and men the wage gap increased (decreased) for reasons not related to differences in the characteristic. We estimate that, if men and women had exactly the same characteristics, women would have earned on average about 8.8 log points less than men in 2006. For 2017, we estimate a gap of 5.07 log points. This implies that men and women receive different wages for the same observed characteristics, but the difference became smaller over time. A closer look at the explanatory variables reveals that, for example, men who cohabited with a partner received a wage premium in 2006 of 6.39 log points in comparison to

[9] Here, we include not only actual labor market experience, but also marital status and a dummy variable that is one if a person is working part-time to proxy for labor market attachment.

[10] Differences in occupations could arise from differences in norms and preferences. Controlling for such differences could thus mask wage gaps arising from such differences.

[11] When we restrict our sample to private sector employees, we observe a similar pattern. See Table 16 in Appendix 1.

women who cohabited with a partner. This premium decreased over time and we estimate it was 0.16 log points in 2017.

Although women's labour force participation rate increased over time, in 2017, it was 7 percentage points (or 16%) less than men's. It is possible that women who are highly productive, and would therefore command a high wage, do not receive a corresponding wage offer. If this were the case, these women most likely decide against participating in the labor market—and women who actually work are those who are, on average, less productive. Or, in contrast, employed women are those who are on average more productive. This would be the case, if the less productive do not receive a sufficiently high wage offer. An observed gender wage gap could be due to such differences in participation due to underlying differences in productivity. We estimate that women who work are positively selected as the estimated coefficient for the inverse Mill's ratio (λ) is negative, i.e., if women who do not work would work, they would receive a lower wage. However, in most years we fail to obtain statistically significant evidence. We also estimate participation equations for men and their selection into the labour market is similar to women's. Again, the estimated coefficients for the inverse Mill's ratio in the wage regressions are negative, however, in most years they are not statistically significant. This can also be seen by the relatively low estimated contribution of the explained and unexplained component due to selection, their sum was about 0.08 log points in 2006 and about − 0.36 log points in 2017. This evidence suggests that the gender wage gap is not due to who among men and women select to participate in the labour market. Rather, as we document in Table 5, differences in labor market experience, occupation and industrial segregation, and labor market attachment are the predominant reasons for the gender wage gap in Austria.

Table 6 Decomposition of the change in the gender wage gap between 2006 and 2017

	Neumark (1988)	Reimers (1983)
Overall change	− 0.0582	− 0.0582
Change in the explained gap	− 0.0207	0.0039
Quantity effect	− 0.0350	− 0.0304
Price effect	0.0066	0.0333
Interaction effect	0.0077	0.0011
Change in the unexplained gap	− 0.0375	− 0.0621
Quantity effect	− 0.0325	− 0.0532
Price effect	− 0.0074	− 0.0132
Interaction effect	0.0024	0.0043

Results from Juhn–Murphy–Pierce decompositions. Dependent variable is the logarithm of hourly gross wages. Explanatory variables used in all decompositions are age, education, experience, health status, household size, nationality, occupation, contract type, sector, position in the firm, region, and firm size

4.4 Juhn–Murphy–Pierce decomposition for 2006 and 2017

In Table 6, we present the decompositions of the change of the gender wage gap over time into three components (Juhn et al. 1991). The three components are calculated separately for the changes in the explained and in the unexplained part of the gender wage gap. The first component attributes changes to changes in the groups' characteristics over time ("quantity effect"), the second component to changes in residual inequality, i.e., changes in prices ("price effect"), and the third component to simultaneous changes in characteristics and prices ("interaction effect").

We estimate that the gender wage gap decreased between 2006 and 2017. Using the decomposition based on pooled regressions as the reference wage distribution, we find that both the explained and the unexplained components decreased. However, the unexplained part decreased more than the explained part. In line with the Oaxaca–Blinder-type decompositions, we find that the gender wage gap in hourly gross wages declined between 2006 and 2017 (− 5.82 log points). The smaller gap was mainly due to a smaller explained component of the wage gap, which is decreasing from about 11.90 in 2006 to 9.82 log points in 2017, a difference of 2.07. The unexplained part of the wage gap decreased from 8.81 in 2006 to 5.07 log points in 2017, a difference of 3.75. The change in the explained part of the gender wage gap and the change of the unexplained part were both due to a substantial shift in observed and unobserved characteristics. Men and women became more similar in those characteristics which are valued in the labor market.[12]

The main factor that narrowed the gender wage gap was the convergence in observed and unobserved characteristics. This can be seen by the two quantity effects, tabulated in column (1) of Table 6, which are − 3.5 log points due to changed observed characteristics and − 3.25 log points due to changes in unobserved characteristics. Reasons for the reduction in unobserved characteristics could have been policies that helped women to catch up with men. For example, the change in the equal treatment law that urged firms to be more open about the wages they pay their employees may have provided better guidance for wage negotiations. Riley-Bowles et al. (2005), for example, show that women tend to negotiate more effectively when there is less ambiguity about wages. Additionally, the change in parental leave subsidies introduced in 2010 or the increase in childcare facilities that started in 2007, may have increased women's labor market attachment.

The view that increased similarity of men's and women's characteristics is the main reason for the decline in the gender wage gap is also supported when we use Reimers's (1983) weighting scheme. We estimate a change of − 3.0 (− 5.3) log points due to changed observed (unobserved) characteristics. Unlike the results from Neumark's (1988) approach, however, this approach shows that the change in the gender wage gap was hardly affected by the changes in the explained part as the increasing similarity between men and women was offset by increasing gender-specific differences in how these characteristics are valued (3.33 log points).

[12] When we restrict our sample to private-sector employees, we observe a similar pattern. See Table 17 in Appendix 1.

Table 7 Gender wage gap decomposition 2006–2017, contribution of characteristics

	Difference in predicted gap	Quantity effect	Price effect	Interaction effect
Total	− 0.0207	− 0.0350	0.0066	0.0077
Origin*	0.0011	0.0010	0.0001	0.0001
Urbanization*	0.0006	0.0000	0.0007	− 0.0002
Education*	− 0.0048	− 0.0054	− 0.0024	0.0030
Experience*	− 0.0154	− 0.0115	− 0.0023	− 0.0016
Occupation*	− 0.0042	− 0.0145	0.0084	0.0018
Industry*	0.0316	− 0.0016	0.0290	0.0042
Leading position*	− 0.0009	0.0031	− 0.0036	− 0.0005
Occ. Status*	− 0.0082	− 0.0009	− 0.0068	− 0.0005
Married	− 0.0009	− 0.0006	0.0003	− 0.0005
Firm size ≥ 10	0.0003	− 0.0023	0.0033	− 0.0007
Part-time	− 0.0083	0.0054	− 0.0105	− 0.0032
Selection	− 0.0117	− 0.0078	− 0.0096	0.0057

Results from Juhn–Murphy–Pierce decompositions. The dependent variable is the logarithm of hourly gross wages. Overall effects are reported for specific groups of regressors such as country of origin, degree of urbanization, education, experience, occupation, industry, leading position, and occupational status

*Indicates overall effects for sets of binary indicators

In Table 7, we show how various variables contributed to the reduction in the explained part of the gender wage gap based on Neumark's (1988) method for decomposing the wage gap. We observe that women caught up in their educational attainments and labor market experience. Smaller gender-specific differences in occupational segregation and in having a leading position reduced the gender wage gap. Most reductions are driven by the quantity effect, where a negative contribution indicates that men and women became more similar. A positive price effect, for example, wage differences associated with wages in economic sectors (industry), widened the wage gap and off-set some gains due to more similarity in observable characteristics. We interpret this as evidence that women receive lower wages when they (increasingly) work in male-dominated industries.

The quantitative most important part of the change in the gender wage gap between 2006 and 2017 is, however, the reduction in the unexplained gap (Table 6). This reduction is mainly determined by fewer differences in unobservable characteristics, which could include negotiation skills. To a smaller extent, the reduction in the unexplained gap is also caused by a price effect, i.e., a smaller difference in how unobserved characteristics are priced.

5 Gap over the business cycle

In a further step of our empirical analysis, we relate the gender wage gap to the business cycle. We use the unemployment rate as a measure of the business cycle and show the correlation with the raw and with the unexplained gender wage gap in

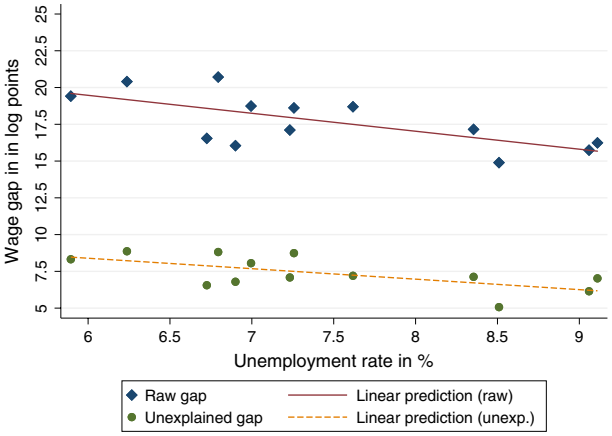

Fig. 2 Gender wage gap and the business cycle. *Notes*: Austrian EU-SILC, 2005–2017 (Austria 2018). Diamonds indicate the unadjusted gender wage gap in gross hourly wages. Circles indicate the residuals from decompositions of the wage gap ("unexplained component"), using the same set of characteristics in each year

Table 8 Estimated correlations

	Raw	HM adjusted	Explained	Unexplained
Constant	0.27	0.32	0.04	0.13
	(0.03)	(0.04)	(0.04)	(0.02)
Unemployment rate	− 1.22	− 1.79	0.33	− 0.71
	(0.39)	(0.48)	(0.48)	(0.26)
R-squared	0.466	0.554	0.041	0.413
Observations	13	13	13	13

This table shows OLS regressions. The dependent variable is a measure of the gender wage gap [raw, Heckman adjusted, explained, and unexplained using Neumark (1988)'s approach]. The explanatory variable is the unemployment rate

Fig. 2. We observe that the unemployment rate is negatively correlated with both the raw and the unexplained gender wage gap. We find that the higher the unemployment rate, the lower is the gender wage gap.

To assess this effect in more detail, we also estimate OLS regressions where we use different measures of the gender wage gap (raw, Heckman adjusted, explained, and unexplained) as dependent variables and the unemployment rate as the explanatory variable. For three of the four dependent variables, we estimate that the gap is negatively correlated with the unemployment rate. The coefficients are statistically significant from zero at conventional levels and support the view that the gender wage gap is responsive to the business cycle. When we use the unexplained wage gap that also controls for selection, we estimate a strong correlation between the two variables. This highlights the necessity to control for selection as job opportunities for men and women change differentially over

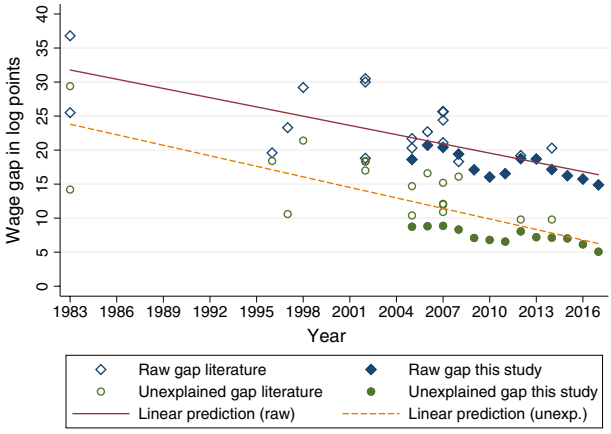

Fig. 3 Gender wage gap between 1983 and 2017. *Notes*: Diamonds indicate the unadjusted gender wage gap in Austria in gross hourly wages, but for 1983, which is based on net hourly wages (Zweimüller and Winter-Ebmer 1994). Circles indicate the residuals from decompositions of the wage gap ("unexplained component") (Zweimüller and Winter-Ebmer 1994; Böheim et al. 2007; Grünberger and Zulehner 2009; Pointner and Stiglbauer 2010; Bundesministerium 2010; Böheim et al. 2013; Grandner and Gstach 2015; Christl and Köppl-Turyna 2020; Arulampalam et al. 2007; Christofides et al. 2013; Redmond and Mcguinness 2019). Full diamonds and full circles are the estimates presented above. The solid and the dashed lines are linear trends

the business cycle. Of the four dependent variables, the explained gender wage gap is positively correlated, but its correlation is not significantly different from zero.[13]

Increased unemployment may lead to more competition for jobs and this could lead to a lower gender wage gap. An alternative view is that unemployment changes the composition of male and female employees, resulting in a more similar distribution of characteristics which are demanded by firms. Because the correlation between the unemployment rate and the raw wage gap is stronger than with the unexplained wage gap, the first explanation seems more plausible (Table 8).

6 Comparison to the literature

Finally, we compare the available estimates of the gender wage gap in Austria in Fig. 3, extending the analyis in Böheim et al. (2013). The estimates from earlier studies (Zweimüller and Winter-Ebmer 1994; Böheim et al. 2007; Grünberger and Zulehner 2009; Pointner and Stiglbauer 2010; Bundesministerium 2010; Böheim et al. 2013; Grandner and Gstach 2015; Christl and Köppl-Turyna 2020; Arulampalam et al. 2007; Christofides et al. 2013; Redmond and Mcguinness 2019) are compared with our results presented above.[14]

[13] When we restrict our sample to private-sector employees, we observe a similar pattern. See Table 18 in Appendix 1.

[14] Several studies made comparisons over time and provide more than one data point. The other studies are represented by one point in the graph.

The earliest study on Austria used data from 1983 (Zweimüller and Winter-Ebmer 1994) and showed a rather large gap of more than 30 log points. In addition, Zweimüller and Winter-Ebmer (1994) used net wages which usually result in a smaller wage gap due to progressive taxation.

Hourly wage data were not regularly collected in Austria and thus there was no further study until the mid-1990s. From then onwards, several studies produced estimates of the gender wage gap. These, however, used different data sets (Mikrozensus, EU-SILC or tax data) or different econometric methods (inclusion of an indicator for women in OLS regressions or different variants of Blinder–Oaxaca decompositions). Despite these differences, it becomes quite apparent that the raw and the unexplained gender wage gap declined over time.

Additionally, we estimate a meta-regression using the results from the studies cited above. We use as the dependent variable the raw gender wage gap and the unexplained gender gap observed in various studies on Austria and as explanatory variables characteristics of the data set and the decomposition method the studies used. Table 9 shows the results from this meta-regression for two samples. The first sample includes all studies and the second sample is limited to studies which used more recent data from 2003 onwards.

Our results in columns (1) and (3) of Table 9 show the results for the raw gender wage gap. We observe that in both samples the raw gender wag gap decreased by about 0.3–0.4 log points per year. This gap is by about 2.0–2.2 log points greater if only data from the private sector was used compared to using data from a combination of public and private sector employees. The use of cross-country data implies a greater raw gap by about 4.7–5.2 log points compared to the use of Austrian data only. We do not estimate statistically significant differences for other sample or study specific characteristics.

In columns (2) and (4) of Table 9, we tabulate the results for the unexplained wage gap. This gap decreased by about 0.6 log points per year. This is slightly more pronounced than the decrease of the raw gap over time. The comparison of the different results show that the unexplained gap is greater for private sector employees than for public sector employees. It can be seen that studies that use only data on private sector employees estimate a greater wage gap than studies that use a combination of both private and public sector employees. This suggests that unobserved characteristics or unequal treatment is more important in the private sector than in the public sector.

The estimated unexplained wage gaps are smaller when the samples consist only of full-time employees. Compared to results that are derived from samples of both part-time and full-time employees, the unexplained gap is about 2.4–4.5 log points smaller, although this result is only significantly different from zero (at conventional levels) in the sample of studies that include older ones.

We also find that the unexplained wage gaps are greater when the results are based only on data from larger firms (more that 10 employees). Compared to all firms, the unexplained gap is greater by about 2.5–2.8 log points. This result is significantly different from zero at conventional levels only for the sample that includes older studies. As expected, the chosen decomposition technique is associated with the size of the unexplained wage gap. Studies that use a Neumark decomposition or which use a binary indicator for the gender result in systematically smaller estimates of the unexplained wage gap than studies that use a male-based Blinder–Oaxaca decomposition. Estimates which are based on a Neumark

Table 9 Meta regressions

	Raw	Unexplained	Raw	Unexplained
Constant	0.2673	0.2742	0.2105	0.1651
	(0.030)	(0.029)	(0.006)	(0.019)
Time trend	− 0.0032	− 0.0055	− 0.0036	− 0.0057
	(0.001)	(0.001)	(0.001)	(0.001)
Private	0.0215	0.0339	0.0199	0.0336
	(0.003)	(0.004)	(0.004)	(0.004)
Net wages	0.0140	− 0.0721		
	(0.022)	(0.028)		
Fulltime workers	− 0.0039	− 0.0447	0.0068	− 0.0243
	(0.022)	(0.020)	(0.018)	(0.013)
Register data	0.0197	− 0.0128	0.0270	− 0.0133
	(0.025)	(0.015)	(0.019)	(0.019)
Large firms	− 0.0110	0.0248	− 0.0178	0.0282
	(0.026)	(0.012)	(0.020)	(0.015)
Cross country sample	0.0518	0.0011	0.0467	0.0049
	(0.009)	(0.024)	(0.017)	(0.025)
Heckman correction		0.0369		0.0223
		(0.016)		(0.021)
Neumark decomposition		− 0.0827		− 0.0604
		(0.024)		(0.023)
Reimers decomposition		− 0.0317		− 0.0265
		(0.015)		(0.013)
Female dummy		− 0.0329		− 0.0325
		(0.014)		(0.021)
Observations	47	47	42	42
R-squared	0.6660	0.7888	0.6867	0.7497

This table shows results from OLS regressions where the dependent variable is an estimate of the Austrian gender wage gap (raw and unexplained) from various studies. The explanatory variables are characteristics of the sample and the decomposition method used by the studies

decomposition are 6.0–8.3 log points smaller and those that use the binary indicator are 3.2–3.3 log points smaller than estimates from a male-based decomposition.

7 Summary and conclusions

We examined the gender wage gap in Austria using EU-SILC data from 2005 to 2017. Using standard decomposition techniques, we decompose the gender wage gap over time. We find that the raw wage gap declined from 18.6 (20.7) log points in 2005 (2006) to 15.0 log points in 2017. Controlling for observed differences between women and men in human capital, occupation, and other explanatory variables, we find that the unexplained part of the gender wage gap decreased substantially over the last ten years. The decrease

of the unexplained gender wage gap between the largest gap in this period (2006) and the most recent gap (2017) ranges from 3.7 log points to 8.5 log points depending on the decomposition approach. Using the method by Neumark (1988), we find that the unexplained gender wage gap shrank from 8.7 (8.8) log points in 2005 (2006) to 5.1 log points in 2017. We find that differences in the observable characteristics such as educational attainment, experience, occupation or industry have become a more important part for the gender wage gap between 2006 and 2017. The remaining part of the wage gap between women and men might be caused by differences in unobserved characteristics, e.g., attitude or commitment, or unfair discrimination against women. Using the approach suggested by Juhn et al. (1991), we find that the main determinant of the shrinking wage gap over time is the relative improvement of women's observed and unobserved characteristics.

Men and women became more similar in observed and unobserved characteristics over time, and this contributed substantially to the reduction of the gender wage gap. One reason for the reduction in observed and unobserved characteristics could have been the implementation of policies that helped women to catch up with men. For example, the change in the equal treatment law that urged firms to be more open about the wages they pay their employees may have provided better guidance for wage negotiations. Riley-Bowles et al. (2005), for example, show that women tend to negotiate more effectively when there is less ambiguity about wages. Additionally, the change in child-care allowance introduced in 2010 or the increase in childcare facilities that started in 2007, may have increased women's labor market attachment.

Our results are consistent with earlier research that showed a narrowing of the gender wage gap over time. For example, Böheim et al. (2013) found that wage differences declined moderately between 2002 and 2007. However, the difference in the raw gender wage gap is still large due to differences in observed and unobserved characteristics between men and women. Labor market experience, occupation and industrial segregation, and labor market attachment are still important aspects where men and women differ, which results in average wage differences.

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Appendix 1: Tables

See Tables 10, 11, 12, 13, 14, 15, 16, 17 and 18.

Table 10 Average wages and usual weekly hours in main job, 2005–2017, by gender in the private sector

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Men													
Wage	14.95	15.13	15.18	14.85	15.78	15.92	15.74	15.64	15.74	15.97	15.91	16.19	15.74
Hours	40.90	40.55	42.02	41.94	41.59	41.21	40.84	41.13	41.19	40.40	40.75	40.66	41.84
Obs.	2052	2307	2551	2031	1997	2176	2116	1921	1956	1951	1969	2005	1996
Women													
Wage	12.17	11.94	11.97	11.79	13.05	13.14	12.85	12.65	12.79	13.10	13.22	13.42	13.16
Hours	33.11	33.44	32.55	32.89	32.74	32.78	32.56	32.14	32.72	31.92	31.62	32.06	32.00
Obs.	1644	1925	2170	1759	1819	1953	1901	1867	1803	1810	1843	1847	1983

Austrian EU-SILC data 2005–2017 (Austria 2018). Gross hourly wages in Euros, deflated using the CPI (base year is 2014)

Table 11 Summary statistics: personal and household characteristics

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Age	38.87 (10.3)	39.46 (10.0)	39.49 (10.4)	40.18 (10.0)	39.88 (10.6)	40.43 (10.2)	39.85 (10.9)	41.07 (10.4)	40.31 (11.2)	40.83 (10.6)	40.59 (11.1)	41.15 (10.8)
Origin												
Austria	0.83 (0.4)	0.85 (0.4)	0.82 (0.4)	0.83 (0.4)	0.82 (0.4)	0.81 (0.4)	0.83 (0.4)	0.79 (0.4)	0.81 (0.4)	0.79 (0.4)	0.79 (0.4)	0.79 (0.4)
EU15	0.03 (0.2)	0.02 (0.2)	0.04 (0.2)	0.03 (0.2)	0.04 (0.2)	0.04 (0.2)	0.04 (0.2)	0.04 (0.2)	0.04 (0.2)	0.04 (0.2)	0.05 (0.2)	0.04 (0.2)
Degree of urbanization												
High	0.35 (0.5)	0.36 (0.5)	0.34 (0.5)	0.39 (0.5)	0.32 (0.5)	0.39 (0.5)	0.27 (0.4)	0.30 (0.5)	0.28 (0.4)	0.31 (0.5)	0.28 (0.5)	0.32 (0.5)
Medium	0.26 (0.4)	0.25 (0.4)	0.25 (0.4)	0.27 (0.4)	0.29 (0.5)	0.27 (0.4)	0.31 (0.5)	0.31 (0.5)	0.30 (0.5)	0.31 (0.5)	0.31 (0.5)	0.30 (0.5)
Low	0.39 (0.5)	0.39 (0.5)	0.41 (0.5)	0.35 (0.5)	0.39 (0.5)	0.34 (0.5)	0.42 (0.5)	0.39 (0.5)	0.42 (0.5)	0.38 (0.5)	0.41 (0.5)	0.37 (0.5)
Formal education												
Compulsory education	0.09 (0.3)	0.15 (0.4)	0.09 (0.3)	0.15 (0.4)	0.10 (0.3)	0.15 (0.4)	0.09 (0.3)	0.13 (0.3)	0.09 (0.3)	0.12 (0.3)	0.07 (0.2)	0.10 (0.3)
Apprentices, Craftsmen	0.51 (0.5)	0.34 (0.5)	0.48 (0.5)	0.29 (0.5)	0.46 (0.5)	0.28 (0.5)	0.48 (0.5)	0.30 (0.5)	0.45 (0.5)	0.28 (0.5)	0.45 (0.5)	0.29 (0.5)
Intermediate voc. education	0.06 (0.2)	0.15 (0.4)	0.06 (0.2)	0.18 (0.4)	0.07 (0.3)	0.18 (0.4)	0.07 (0.2)	0.19 (0.4)	0.09 (0.3)	0.20 (0.4)	0.08 (0.3)	0.21 (0.4)
Upper secondary (academic)	0.05 (0.2)	0.07 (0.3)	0.05 (0.2)	0.07 (0.3)	0.05 (0.2)	0.08 (0.3)	0.05 (0.2)	0.05 (0.2)	0.04 (0.2)	0.06 (0.2)	0.05 (0.2)	0.05 (0.2)

Table 11 (continued)

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Upper secondary (other)	0.17 (0.4)	0.15 (0.4)	0.17 (0.4)	0.16 (0.4)	0.18 (0.4)	0.15 (0.4)	0.19 (0.4)	0.17 (0.4)	0.17 (0.4)	0.15 (0.4)	0.18 (0.4)	0.14 (0.3)
Academic degree	0.11 (0.3)	0.14 (0.4)	0.14 (0.3)	0.15 (0.4)	0.13 (0.3)	0.15 (0.4)	0.13 (0.3)	0.16 (0.4)	0.15 (0.4)	0.20 (0.4)	0.17 (0.4)	0.21 (0.4)
Enrolled	0.02 (0.1)	0.03 (0.2)	0.02 (0.1)	0.03 (0.2)	0.03 (0.2)	0.03 (0.2)	0.03 (0.2)	0.03 (0.2)	0.03 (0.2)	0.04 (0.2)	0.04 (0.2)	0.04 (0.2)
Household (presence of)												
Cohabiting partner	0.68 (0.5)	0.66 (0.5)	0.65 (0.5)	0.66 (0.5)	0.66 (0.5)	0.66 (0.5)	0.66 (0.5)	0.68 (0.5)	0.67 (0.5)	0.68 (0.5)	0.67 (0.5)	0.69 (0.5)
Employed partner	0.42 (0.5)	0.54 (0.5)	0.44 (0.5)	0.56 (0.5)	0.45 (0.5)	0.56 (0.5)	0.46 (0.5)	0.57 (0.5)	0.47 (0.5)	0.58 (0.5)	0.49 (0.5)	0.61 (0.5)
Children aged 0–2 years	0.11 (0.4)	0.04 (0.2)	0.12 (0.4)	0.04 (0.2)	0.12 (0.4)	0.04 (0.2)	0.12 (0.4)	0.04 (0.2)	0.12 (0.4)	0.05 (0.2)	0.11 (0.4)	0.04 (0.2)
Children aged 3–5 years	0.11 (0.3)	0.08 (0.3)	0.10 (0.3)	0.09 (0.3)	0.11 (0.3)	0.08 (0.3)	0.10 (0.3)	0.08 (0.3)	0.10 (0.3)	0.08 (0.3)	0.11 (0.4)	0.10 (0.3)
Children aged 6–9 years	0.13 (0.4)	0.13 (0.4)	0.12 (0.4)	0.12 (0.4)	0.12 (0.4)	0.11 (0.4)	0.13 (0.4)	0.13 (0.4)	0.13 (0.4)	0.12 (0.4)	0.13 (0.4)	0.12 (0.4)
Children aged 10–18 years	0.22 (0.5)	0.26 (0.6)	0.21 (0.5)	0.23 (0.5)	0.19 (0.5)	0.23 (0.5)	0.18 (0.5)	0.22 (0.5)	0.18 (0.5)	0.22 (0.5)	0.20 (0.5)	0.22 (0.5)

Table 11 (continued)

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Health status												
Bad general health	0.02 (0.1)	0.02 (0.1)	0.02 (0.2)	0.03 (0.2)	0.02 (0.2)	0.03 (0.2)	0.03 (0.2)	0.03 (0.2)	0.02 (0.1)	0.03 (0.2)	0.02 (0.1)	0.02 (0.2)
Fair general health	0.12 (0.3)	0.12 (0.3)	0.15 (0.4)	0.15 (0.4)	0.15 (0.4)	0.15 (0.4)	0.16 (0.4)	0.17 (0.4)	0.15 (0.4)	0.14 (0.3)	0.16 (0.4)	0.15 (0.4)
Good general health	0.86 (0.3)	0.86 (0.3)	0.83 (0.4)	0.82 (0.4)	0.82 (0.4)	0.82 (0.4)	0.82 (0.4)	0.80 (0.4)	0.83 (0.4)	0.83 (0.4)	0.82 (0.4)	0.82 (0.4)
Limit. health problems	0.03 (0.2)	0.03 (0.2)	0.02 (0.1)	0.03 (0.2)	0.02 (0.2)	0.02 (0.2)	0.03 (0.2)	0.02 (0.1)	0.02 (0.2)	0.03 (0.2)	0.02 (0.1)	0.04 (0.2)
Chronic health problems	0.14 (0.3)	0.15 (0.4)	0.21 (0.4)	0.21 (0.4)	0.23 (0.4)	0.25 (0.4)	0.24 (0.4)	0.25 (0.4)	0.24 (0.4)	0.25 (0.4)	0.27 (0.4)	0.30 (0.5)
Experience	20.55 (11.0)	17.34 (9.9)	21.48 (11.0)	18.98 (10.1)	21.99 (11.3)	19.15 (10.1)	21.96 (11.6)	19.59 (10.4)	22.53 (11.9)	19.36 (10.5)	22.59 (11.9)	19.91 (10.7)
Observations	2991	2567	2303	2094	2445	2315	2280	2148	2276	2218	2308	2344

Based on EU-SILC data 2005-2017. Means of personal characteristics for men and women in 2007, 2009, 2011, 2013, 2015 and 2017. Standard deviations in parentheses

Table 12 Summary statistics: job-related characteristics

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Occupational status												
Blue-collar worker	0.44 (0.5)	0.26 (0.4)	0.40 (0.5)	0.22 (0.4)	0.43 (0.5)	0.22 (0.4)	0.43 (0.5)	0.24 (0.4)	0.43 (0.5)	0.22 (0.4)	0.40 (0.5)	0.21 (0.4)
White-collar worker	0.43 (0.5)	0.60 (0.5)	0.47 (0.5)	0.65 (0.5)	0.45 (0.5)	0.60 (0.5)	0.44 (0.5)	0.61 (0.5)	0.45 (0.5)	0.63 (0.5)	0.49 (0.5)	0.66 (0.5)
Civil servant	0.14 (0.3)	0.14 (0.3)	0.12 (0.3)	0.13 (0.3)	0.12 (0.3)	0.18 (0.4)	0.13 (0.3)	0.15 (0.4)	0.12 (0.3)	0.15 (0.4)	0.12 (0.3)	0.14 (0.3)
Occupation												
Managers	0.04 (0.2)	0.01 (0.1)	0.06 (0.2)	0.02 (0.2)	0.08 (0.3)	0.03 (0.2)	0.06 (0.2)	0.03 (0.2)	0.05 (0.2)	0.03 (0.2)	0.07 (0.2)	0.03 (0.2)
Professionals	0.06 (0.2)	0.09 (0.3)	0.09 (0.3)	0.12 (0.3)	0.13 (0.3)	0.17 (0.4)	0.14 (0.3)	0.16 (0.4)	0.15 (0.4)	0.19 (0.4)	0.15 (0.4)	0.19 (0.4)
Technicians	0.21 (0.4)	0.12 (0.3)	0.21 (0.4)	0.19 (0.4)	0.19 (0.4)	0.19 (0.4)	0.19 (0.4)	0.21 (0.4)	0.19 (0.4)	0.21 (0.4)	0.20 (0.4)	0.20 (0.4)
Clerical support	0.12 (0.3)	0.29 (0.5)	0.09 (0.3)	0.25 (0.4)	0.06 (0.2)	0.19 (0.4)	0.06 (0.2)	0.16 (0.4)	0.06 (0.2)	0.15 (0.4)	0.06 (0.2)	0.16 (0.4)
Service and Sales	0.13 (0.3)	0.28 (0.4)	0.08 (0.3)	0.22 (0.4)	0.10 (0.3)	0.23 (0.4)	0.10 (0.3)	0.24 (0.4)	0.10 (0.3)	0.24 (0.4)	0.10 (0.3)	0.23 (0.4)
Skilled agricult.	0.01 (0.1)	0.01 (0.1)	0.01 (0.1)	0.01 (0.1)	0.01 (0.1)	0.01 (0.1)	0.01 (0.1)	0.00 (0.1)	0.01 (0.1)	0.01 (0.1)	0.01 (0.1)	0.00 (0.1)
Skilled trades	0.24 (0.4)	0.04 (0.2)	0.22 (0.4)	0.01 (0.1)	0.24 (0.4)	0.03 (0.2)	0.26 (0.4)	0.03 (0.2)	0.24 (0.4)	0.02 (0.1)	0.25 (0.4)	0.02 (0.2)
Plant/machine operatives	0.09 (0.3)	0.01 (0.1)	0.12 (0.3)	0.01 (0.1)	0.11 (0.3)	0.02 (0.1)	0.11 (0.3)	0.02 (0.1)	0.12 (0.3)	0.02 (0.1)	0.10 (0.3)	0.03 (0.2)
Elementary	0.10 (0.3)	0.16 (0.4)	0.12 (0.3)	0.15 (0.4)	0.08 (0.3)	0.13 (0.3)	0.07 (0.3)	0.14 (0.3)	0.07 (0.3)	0.13 (0.3)	0.07 (0.3)	0.13 (0.3)
Industry												
Primary sector	0.03 (0.2)	0.02 (0.1)	0.01 (0.1)	0.01 (0.1)	0.02 (0.1)	0.01 (0.1)	0.01 (0.1)	0.01 (0.1)	0.02 (0.1)	0.01 (0.1)	0.01 (0.1)	0.01 (0.1)
Manufacturing	0.32 (0.5)	0.16 (0.4)	0.24 (0.4)	0.08 (0.3)	0.26 (0.4)	0.10 (0.3)	0.25 (0.4)	0.10 (0.3)	0.26 (0.4)	0.09 (0.3)	0.27 (0.4)	0.09 (0.3)
Energy	0.03 (0.2)	0.01 (0.1)	0.02 (0.1)	0.01 (0.1)	0.02 (0.1)	0.01 (0.1)	0.02 (0.1)	0.00 (0.1)	0.03 (0.2)	0.01 (0.1)	0.02 (0.1)	0.00 (0.1)
Construction	0.12 (0.3)	0.02 (0.1)	0.15 (0.4)	0.03 (0.2)	0.12 (0.3)	0.03 (0.2)	0.16 (0.4)	0.04 (0.2)	0.13 (0.3)	0.02 (0.1)	0.13 (0.3)	0.02 (0.1)
Trade	0.08 (0.3)	0.15 (0.4)	0.15 (0.4)	0.18 (0.4)	0.14 (0.3)	0.18 (0.4)	0.12 (0.3)	0.19 (0.4)	0.11 (0.3)	0.17 (0.4)	0.11 (0.3)	0.17 (0.4)
Transport, ICT	0.06 (0.2)	0.02 (0.1)	0.11 (0.3)	0.04 (0.2)	0.11 (0.3)	0.05 (0.2)	0.13 (0.3)	0.04 (0.2)	0.12 (0.3)	0.04 (0.2)	0.11 (0.3)	0.03 (0.2)
Accommodation, Food	0.03 (0.2)	0.06 (0.2)	0.03 (0.2)	0.07 (0.3)	0.04 (0.2)	0.07 (0.2)	0.03 (0.2)	0.06 (0.2)	0.04 (0.2)	0.07 (0.2)	0.04 (0.2)	0.08 (0.3)
Finance, Real Estate	0.04 (0.2)	0.05 (0.2)	0.05 (0.2)	0.06 (0.2)	0.04 (0.2)	0.05 (0.2)	0.04 (0.2)	0.04 (0.2)	0.03 (0.2)	0.05 (0.2)	0.03 (0.2)	0.04 (0.2)
Professional services	0.08 (0.3)	0.09 (0.3)	0.06 (0.2)	0.11 (0.3)	0.06 (0.2)	0.10 (0.3)	0.07 (0.3)	0.09 (0.3)	0.07 (0.3)	0.09 (0.3)	0.08 (0.3)	0.09 (0.3)

Table 12 (continued)

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Public services	0.14 (0.3)	0.31 (0.5)	0.16 (0.4)	0.36 (0.5)	0.17 (0.4)	0.37 (0.5)	0.15 (0.4)	0.38 (0.5)	0.18 (0.4)	0.41 (0.5)	0.17 (0.4)	0.38 (0.5)
Other services	0.06 (0.2)	0.12 (0.3)	0.03 (0.2)	0.04 (0.2)	0.03 (0.2)	0.05 (0.2)	0.02 (0.1)	0.04 (0.2)	0.02 (0.2)	0.05 (0.2)	0.02 (0.2)	0.07 (0.3)
Other characteristics												
Managerial position	0.43 (0.5)	0.27 (0.4)	0.53 (0.5)	0.37 (0.5)	0.51 (0.5)	0.37 (0.5)	0.53 (0.5)	0.36 (0.5)	0.52 (0.5)	0.36 (0.5)	0.51 (0.5)	0.37 (0.5)
Highly skilled/senior employees	0.14 (0.3)	0.07 (0.3)	0.17 (0.4)	0.11 (0.3)	0.22 (0.4)	0.12 (0.3)	0.20 (0.4)	0.12 (0.3)	0.20 (0.4)	0.12 (0.3)	0.21 (0.4)	0.12 (0.3)
Firm size > 10	0.81 (0.4)	0.67 (0.5)	0.78 (0.4)	0.63 (0.5)	0.78 (0.4)	0.68 (0.5)	0.78 (0.4)	0.69 (0.5)	0.79 (0.4)	0.70 (0.5)	0.81 (0.4)	0.71 (0.5)
Part-time	0.05 (0.2)	0.41 (0.5)	0.05 (0.2)	0.43 (0.5)	0.06 (0.2)	0.43 (0.5)	0.05 (0.2)	0.44 (0.5)	0.06 (0.2)	0.49 (0.5)	0.07 (0.3)	0.49 (0.5)
Observations	2991	2567	2303	2094	2445	2315	2280	2148	2276	2218	2308	2344

Based on EU-SILC data 2005-2017. Means of job-related characteristics for men and women in 2007, 2009, 2011, 2013, 2015 and 2017. Standard deviations in parentheses

Table 13 Heckman wage equation

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Log. gross hourly earnings												
Origin (Ref: Non-EU15)												
Austria	0.09	0.08	0.15	0.12	0.09	0.08	0.14	0.08	0.13	0.05	0.11	0.05
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
EU15	0.15	0.06	0.11	0.11	0.11	0.04	0.15	0.06	0.06	− 0.00	0.07	0.09
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Degree of urbanization (Ref: dense)												
Medium	0.02	− 0.01	− 0.00	0.00	− 0.03	− 0.04	0.04	− 0.01	0.03	0.00	0.04	− 0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Low	− 0.03	− 0.08	− 0.06	− 0.02	− 0.02	− 0.05	− 0.01	− 0.03	0.01	− 0.02	− 0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Formal education (Ref: compulsory)												
Apprentices, Craftsmen	0.03	0.02	− 0.01	0.02	0.05	0.02	0.00	0.03	0.04	− 0.01	0.00	− 0.02
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Intermediate voc. education	0.10	0.13	0.04	0.17	0.09	0.07	0.06	0.11	0.09	0.06	0.08	0.06
	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Upper secondary (academic)	0.20	0.17	0.19	0.25	0.26	0.07	0.11	0.16	0.06	0.02	0.12	0.07
	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Upper secondary (other)	0.19	0.15	0.12	0.23	0.11	0.11	0.09	0.13	0.11	0.07	0.11	0.12
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Academic degree	0.31	0.29	0.28	0.40	0.23	0.28	0.19	0.24	0.18	0.21	0.19	0.17
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)

Table 13 (continued)

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Experience												
Experience	0.01	0.02	0.02	0.02	0.01	0.02	0.02	0.01	0.02	0.01	0.02	0.02
	(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 sq.	− 0.01	− 0.02	− 0.02	− 0.01	− 0.02	− 0.02	− 0.02	− 0.01	− 0.03	− 0.01	− 0.02	− 0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Occupational status (Ref: White-collar)												
Blue-collar worker	− 0.06	− 0.07	− 0.09	− 0.05	− 0.09	− 0.06	− 0.07	− 0.13	− 0.08	− 0.06	− 0.09	0.09
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Civil servant	0.02	0.10	0.07	0.06	0.06	0.07	0.06	0.04	0.05	0.05	0.05	0.09
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Occupation (Ref: Service workers)												
Managers	0.06	0.15	0.14	0.19	0.29	0.31	0.24	0.26	0.23	0.27	0.27	0.23
	(0.05)	(0.07)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)	(0.04)
Professionals	0.14	0.24	0.21	0.27	0.27	0.25	0.22	0.26	0.19	0.27	0.27	0.25
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Technicians	0.10	0.16	0.13	0.13	0.18	0.22	0.12	0.18	0.09	0.20	0.13	0.20
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
Clerical support	0.09	0.10	0.05	0.10	0.08	0.14	0.02	0.10	0.04	0.09	− 0.00	0.14
	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)
Skilled agricult.	− 0.23	0.14	− 0.09	0.01	− 0.33	− 0.11	− 0.15	− 0.05	− 0.08	− 0.09	− 0.17	0.01
	(0.10)	(0.11)	(0.11)	(0.05)	(0.11)	(0.05)	(0.08)	(0.05)	(0.07)	(0.17)	(0.06)	(0.10)
Skilled trades	0.03	0.11	0.07	− 0.10	0.10	0.12	0.02	0.11	0.00	− 0.03	0.10	0.03
	(0.03)	(0.04)	(0.03)	(0.12)	(0.03)	(0.10)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)

Table 13 (continued)

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Plant/machine operatives	− 0.02	0.08	0.04	− 0.07	0.07	− 0.02	− 0.00	0.08	− 0.09	− 0.01	0.04	− 0.01
	(0.04)	(0.05)	(0.04)	(0.10)	(0.04)	(0.05)	(0.03)	(0.05)	(0.04)	(0.07)	(0.04)	(0.04)
Elementary	− 0.08	0.01	− 0.07	− 0.07	0.00	− 0.06	− 0.10	− 0.01	− 0.07	− 0.04	− 0.02	− 0.03
	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Industry (Ref: Prof. services)												
Primary sector	0.01	− 0.20	− 0.09	0.04	− 0.10	0.00	− 0.10	0.12	0.04	− 0.07	0.07	0.16
	(0.06)	(0.06)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.06)	(0.08)	(0.10)	(0.06)	(0.12)
Manufacturing	− 0.01	− 0.06	0.15	0.12	0.08	0.07	0.10	0.11	0.13	0.14	0.12	0.07
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Energy	0.00	− 0.14	0.14	0.19	0.07	0.30	0.11	0.25	0.12	0.06	0.20	0.19
	(0.04)	(0.10)	(0.07)	(0.06)	(0.05)	(0.13)	(0.04)	(0.08)	(0.05)	(0.07)	(0.05)	(0.08)
Construction	− 0.01	− 0.08	0.10	0.09	0.08	0.03	0.09	0.10	0.10	0.10	0.08	0.07
	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.06)	(0.03)	(0.05)
Trade	− 0.08	− 0.05	0.05	0.01	0.02	0.03	− 0.00	0.04	0.02	0.02	0.00	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Transport, ICT	− 0.04	− 0.02	0.06	0.02	0.02	0.01	0.02	0.04	0.04	0.02	0.03	0.06
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
Accommodation, Food	− 0.22	− 0.16	− 0.07	− 0.12	− 0.12	− 0.04	− 0.12	0.00	− 0.16	− 0.09	− 0.15	− 0.06
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)
Finance, Real Estate	0.10	0.14	0.27	0.15	0.16	0.17	0.12	0.19	0.18	0.20	0.17	0.11
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Public services	− 0.03	− 0.01	0.00	0.04	− 0.00	0.03	− 0.03	0.05	− 0.03	0.01	− 0.01	0.01
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)

Table 13 (continued)

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Other services	− 0.13	− 0.13	− 0.09	0.04	− 0.04	− 0.01	− 0.01	0.02	0.04	− 0.02	− 0.08	− 0.04
	(0.04)	(0.04)	(0.06)	(0.06)	(0.07)	(0.05)	(0.07)	(0.03)	(0.05)	(0.03)	(0.06)	(0.04)
Hierarchy												
Managerial position	0.09	0.08	0.07	0.03	0.09	0.05	0.07	0.04	0.06	0.05	0.06	0.07
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Highly skilled/senior employees	0.11	0.09	0.11	0.09	0.12	0.13	0.15	0.13	0.16	0.17	0.10	0.15
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Other variables												
Cohabiting partner	0.06	− 0.01	0.07	0.00	0.06	− 0.02	0.02	− 0.01	0.05	− 0.01	0.03	0.03
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Firm size > 10	0.11	0.05	0.09	0.06	0.09	0.06	0.08	0.12	0.11	0.09	0.09	0.11
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Part-time	− 0.03	− 0.01	− 0.03	0.02	− 0.05	0.03	− 0.07	0.05	0.01	0.08	− 0.05	0.03
	(0.05)	(0.01)	(0.04)	(0.02)	(0.04)	(0.01)	(0.04)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
Constant	2.13	2.01	2.01	1.89	2.05	1.99	2.06	1.98	1.98	2.01	2.01	1.94
	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
λ	− 0.02	0.03	− 0.03	0.01	− 0.15	− 0.01	− 0.06	− 0.10	− 0.05	− 0.02	− 0.02	− 0.01
p value of λ	0.54	0.13	0.41	0.66	0.00	0.71	0.13	0.00	0.16	0.49	0.54	0.76
Observations	3644.00	3969.00	2907.00	3161.00	3034.00	3342.00	2814.00	3120.00	2819.00	3113.00	2772.00	3090.00

Results from maximum likelihood estimations based on EU-SILC 2005–2017. Dependent variable is the logarithm of hourly gross wages. Standard errors in parentheses

Table 14 Heckman participation equation

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Participation												
Origin (Ref: Non-EU15)												
Austria	0.06	− 0.01	0.08	− 0.13	0.22	− 0.19	0.27	− 0.07	0.11	0.15	0.07	0.10
	(0.11)	(0.09)	(0.12)	(0.11)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)	(0.09)	(0.12)	(0.10)
EU15	0.05	− 0.11	0.46	0.05	0.20	− 0.05	0.27	0.15	0.09	0.06	− 0.26	0.06
	(0.35)	(0.22)	(0.25)	(0.21)	(0.25)	(0.20)	(0.23)	(0.20)	(0.23)	(0.17)	(0.20)	(0.22)
Degree of urbanization (Ref: dense)												
Medium	0.07	0.09	0.16	0.04	0.38	− 0.04	0.09	0.02	0.21	− 0.01	0.31	0.09
	(0.09)	(0.07)	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)
Low	0.16	0.07	0.14	− 0.07	0.28	− 0.15	0.15	0.02	0.25	− 0.01	0.41	0.01
	(0.08)	(0.07)	(0.09)	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.10)	(0.09)
Formal education (Ref: compulsory)												
Apprentices, Craftsmen	0.24	0.06	0.16	0.11	0.23	− 0.02	0.24	0.05	0.12	− 0.00	0.36	0.09
	(0.11)	(0.08)	(0.11)	(0.10)	(0.11)	(0.09)	(0.12)	(0.10)	(0.12)	(0.10)	(0.15)	(0.12)
Intermediate voc. education	0.66	0.21	0.46	0.46	0.74	0.43	0.77	0.33	0.28	0.36	0.50	0.44
	(0.17)	(0.10)	(0.18)	(0.12)	(0.19)	(0.11)	(0.19)	(0.11)	(0.16)	(0.11)	(0.21)	(0.13)
Upper secondary (academic)	0.30	0.30	0.14	0.24	0.10	0.23	0.20	0.17	0.44	0.48	0.38	0.39
	(0.16)	(0.12)	(0.16)	(0.13)	(0.14)	(0.13)	(0.16)	(0.14)	(0.18)	(0.15)	(0.19)	(0.16)
Upper secondary (other)	0.44	0.30	0.35	0.57	0.46	0.44	0.49	0.46	0.32	0.53	0.54	0.32
	(0.14)	(0.10)	(0.13)	(0.11)	(0.12)	(0.11)	(0.14)	(0.11)	(0.13)	(0.12)	(0.16)	(0.13)
Academic degree	0.63	0.67	0.86	0.81	0.95	0.88	0.66	0.67	0.73	0.86	0.84	0.62
	(0.17)	(0.11)	(0.17)	(0.12)	(0.15)	(0.12)	(0.16)	(0.13)	(0.16)	(0.12)	(0.18)	(0.13)

Table 14 (continued)

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Experience												
Experience	0.11	0.17	0.15	0.19	0.15	0.20	0.12	0.18	0.13	0.14	0.12	0.17
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Experience sq.	− 0.12	− 0.31	− 0.20	− 0.32	− 0.18	− 0.33	− 0.10	− 0.29	− 0.14	− 0.22	− 0.13	− 0.25
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Age category (Ref: 20–24 years)												
25–34 years	− 0.25	− 0.40	− 0.19	− 0.13	− 0.30	− 0.29	− 0.19	− 0.30	− 0.23	− 0.07	− 0.26	− 0.48
	(0.13)	(0.11)	(0.14)	(0.12)	(0.14)	(0.13)	(0.15)	(0.13)	(0.14)	(0.15)	(0.15)	(0.14)
35–44 years	− 0.81	− 0.90	− 0.91	− 0.85	− 1.17	− 1.08	− 0.80	− 0.91	− 1.12	− 0.66	− 1.26	− 1.13
	(0.18)	(0.13)	(0.22)	(0.16)	(0.21)	(0.16)	(0.22)	(0.16)	(0.20)	(0.17)	(0.22)	(0.18)
45–54 years	− 1.62	− 1.43	− 1.62	− 1.34	− 1.83	− 1.58	− 1.83	− 1.58	− 1.91	− 1.08	− 1.85	− 1.70
	(0.24)	(0.14)	(0.25)	(0.16)	(0.26)	(0.17)	(0.27)	(0.17)	(0.25)	(0.18)	(0.28)	(0.19)
55–65 years	− 2.80	− 2.57	− 2.23	− 2.42	− 2.68	− 2.62	− 2.69	− 2.43	− 2.66	− 2.04	− 2.46	− 2.50
	(0.30)	(0.18)	(0.29)	(0.19)	(0.31)	(0.19)	(0.32)	(0.19)	(0.31)	(0.20)	(0.33)	(0.20)
Health status												
Limit. health problems	− 0.41	− 0.38	− 0.85	− 0.86	− 0.57	− 0.77	− 0.92	− 0.85	− 0.81	− 0.59	− 0.82	− 0.68
	(0.14)	(0.15)	(0.16)	(0.18)	(0.14)	(0.15)	(0.15)	(0.16)	(0.15)	(0.15)	(0.17)	(0.17)
Fair general health	0.69	0.41	0.45	0.08	0.53	0.63	0.41	0.36	0.56	0.30	0.51	0.73
	(0.16)	(0.19)	(0.16)	(0.20)	(0.15)	(0.16)	(0.16)	(0.16)	(0.16)	(0.17)	(0.20)	(0.20)
Good general health	1.15	0.75	0.84	0.24	0.93	0.96	0.68	0.58	1.02	0.68	0.88	0.78
	(0.17)	(0.21)	(0.17)	(0.20)	(0.15)	(0.16)	(0.17)	(0.16)	(0.17)	(0.17)	(0.21)	(0.20)
Chronic health problems	− 0.11	− 0.03	− 0.19	− 0.31	− 0.32	− 0.02	− 0.37	− 0.22	− 0.06	− 0.17	− 0.02	− 0.18
	(0.10)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)

Table 14 (continued)

	2007		2009		2011		2013		2015		2017	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Household (presence of)												
Cohabiting partner	0.17	− 0.15	0.08	− 0.33	0.08	− 0.19	0.08	0.09	0.23	− 0.17	0.25	0.08
	(0.10)	(0.09)	(0.12)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.12)	(0.11)	(0.13)	(0.12)
Employed partner	0.18	0.20	0.13	0.34	0.16	0.29	0.34	0.14	0.26	0.33	0.26	0.29
	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)	(0.12)	(0.11)
Children aged 0–2 years	− 0.04	− 0.97	− 0.06	− 0.93	0.14	− 0.76	0.25	− 0.80	− 0.16	− 0.77	− 0.19	− 1.03
	(0.13)	(0.10)	(0.12)	(0.12)	(0.15)	(0.13)	(0.14)	(0.13)	(0.15)	(0.13)	(0.14)	(0.12)
Children aged 3–5 years	0.13	− 0.41	0.14	− 0.35	0.26	− 0.37	0.01	− 0.50	0.11	− 0.34	0.26	− 0.12
	(0.13)	(0.08)	(0.15)	(0.10)	(0.16)	(0.10)	(0.13)	(0.10)	(0.16)	(0.10)	(0.15)	(0.11)
Children aged 6–9 years	− 0.04	− 0.24	− 0.03	− 0.35	0.05	− 0.35	0.05	− 0.11	− 0.02	− 0.29	− 0.07	− 0.27
	(0.11)	(0.07)	(0.11)	(0.08)	(0.12)	(0.09)	(0.11)	(0.08)	(0.11)	(0.08)	(0.13)	(0.09)
Children aged 10–18 years	0.08	− 0.10	− 0.07	− 0.13	− 0.01	0.00	− 0.02	− 0.15	− 0.02	− 0.03	0.14	− 0.13
	(0.09)	(0.05)	(0.07)	(0.06)	(0.08)	(0.07)	(0.08)	(0.06)	(0.08)	(0.06)	(0.11)	(0.07)
Other variables												
Enrolled	− 1.56	− 1.46	− 1.37	− 1.20	− 1.22	− 1.51	− 1.29	− 1.28	− 1.50	− 1.57	− 1.13	− 1.29
	(0.14)	(0.12)	(0.14)	(0.13)	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Constant	− 0.95	− 0.70	− 1.02	− 0.39	− 1.38	− 0.86	− 0.92	− 0.76	− 1.12	− 0.69	− 1.15	− 0.88
	(0.22)	(0.25)	(0.24)	(0.25)	(0.21)	(0.21)	(0.24)	(0.21)	(0.23)	(0.22)	(0.28)	(0.26)
λ	− 0.02	0.03	− 0.03	0.01	− 0.15	− 0.01	− 0.06	− 0.10	− 0.05	− 0.02	− 0.02	− 0.01
p value of λ	0.54	0.13	0.41	0.66	0.00	0.71	0.13	0.00	0.16	0.49	0.54	0.76
Observations	3644.00	3969.00	2907.00	3161.00	3034.00	3342.00	2814.00	3120.00	2819.00	3113.00	2772.00	3090.00

Results from probit regressions based on EU-SILC 2005–2017. Dependent variable is a dummy variable for being employed. Standard errors in parentheses

Table 15 Blinder–Oaxaca decomposition from 2005 until 2017, private sector

Year	Wage difference	Difference over time	Explained gap	Difference over time	Unexplained gap	Difference over time
2005	0.2156		0.1169		0.0987	
2006	0.2366	0.0210	0.1421	0.0252	0.0945	− 0.0042
2007	0.2307	− 0.0059	0.1361	− 0.0060	0.0946	0.0001
2008	0.2268	− 0.0040	0.1380	0.0019	0.0888	− 0.0058
2009	0.1893	− 0.0375	0.1155	− 0.0225	0.0738	− 0.0150
2010	0.1798	− 0.0094	0.1182	0.0027	0.0617	− 0.0121
2011	0.1903	0.0105	0.1351	0.0169	0.0552	− 0.0064
2012	0.2071	0.0167	0.1307	− 0.0045	0.0764	0.0212
2013	0.2017	− 0.0053	0.1326	0.0019	0.0692	− 0.0072
2014	0.1943	− 0.0074	0.1252	− 0.0074	0.0692	− 0.0000
2015	0.1795	− 0.0148	0.1155	− 0.0097	0.0641	− 0.0051
2016	0.1848	0.0052	0.1232	0.0078	0.0616	− 0.0025
2017	0.1698	− 0.0149	0.1192	− 0.0040	0.0506	− 0.0110
2006	0.2366		0.1421		0.0945	
2017	0.1698	− 0.0668	0.1192	− 0.0229	0.0506	− 0.0439

Results from Blinder–Oaxaca decompositions. Dependent variable is the logarithm of hourly gross wages

Table 16 Decomposition of wage differentials in 2006 and 2017, private sector

Difference in coefficients	(1)	(2)	(3)	(4)	(5)
Estimated value 2006	0.2366	0.1873	0.1319	0.1097	0.0945
in % of the mean wage differential	100.0	79.2	55.8	46.4	39.9
Estimated value 2017	0.1698	0.1539	0.0982	0.0607	0.0506
in % of the mean wage differential	100.0	90.6	57.8	35.7	29.8
Education		×	×	×	×
Experience, marital status, part-time			×	×	×
Status, occupation, industry, region, citizenship				×	×
Firm size, hierarchy					×

Results from Blinder–Oaxaca decompositions. Dependent variable is the logarithm of hourly gross wages

Table 17 Gender wage gap decompositions between 2006 and 2017, private sector

Overall change	− 0.0668
Change in the explained gap	− 0.0229
Quantity effect	− 0.0284
Price effect	− 0.0014
Interaction effect	0.0070
Change in the unexplained gap	− 0.0439
Quantity effect	− 0.0391
Price effect	− 0.0079
Interaction effect	0.0030

Results from Juhn–Murphy–Pierce decompositions. Dependent variable is the logarithm of hourly gross wages

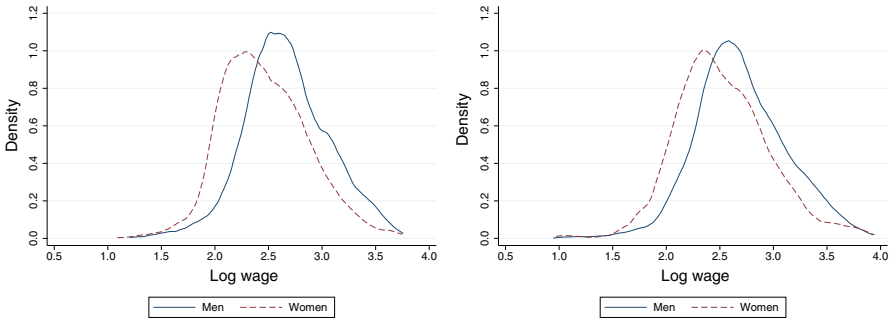
Table 18 Estimated correlations, private sector

	Raw	HM adjusted	Explained	Unexplained
Constant	0.31	0.37	0.07	0.14
	(0.03)	(0.04)	(0.05)	(0.03)
Unemployment rate	− 1.44	− 2.16	0.32	− 0.89
	(0.45)	(0.60)	(0.64)	(0.38)
R-squared	0.482	0.541	0.022	0.332
Observations	13	13	13	13

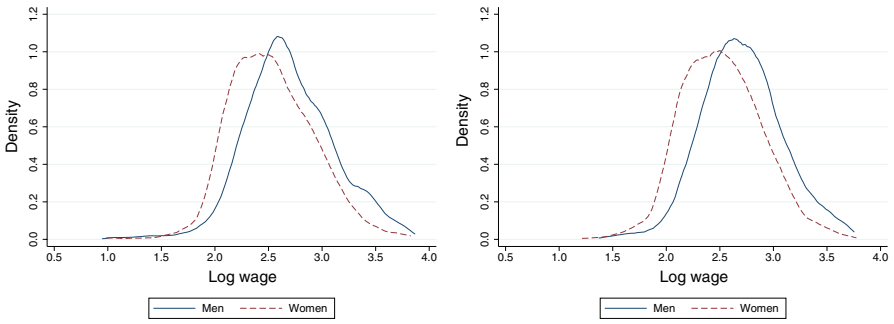
This table shows OLS regressions. The dependent variable is a measure of the gender wage gap (raw, Heckman adjusted, explained, and unexplained). The explanatory variable is the unemployment rate

Appendix 2: Figures

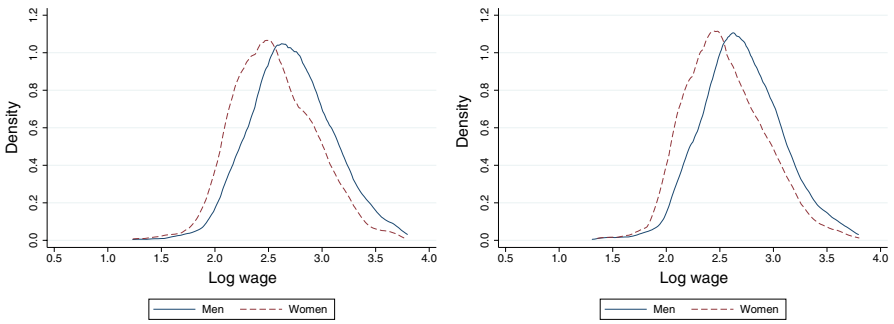
See Figs. 4, 5 and 6.



(a) 2007 **(b)** 2009



(c) 2011 **(d)** 2013



(e) 2015 **(f)** 2017

Fig. 4 Distribution of Log Wages. *Notes:* Based on EU-SILC data 2005–2017. The graphs show the distribution of log male and female gross hourly wages in 2007, 2009, 2011, 2013, 2015, and 2017. Wages deflated using the CPI (base year is 2014)

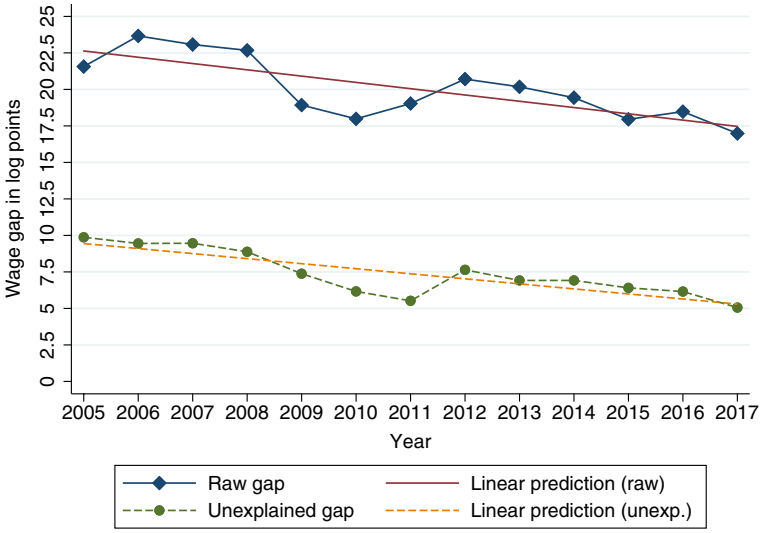


Fig. 5 Gender wage gap in Austria, 2005–2017, private sector. *Notes*: Austrian EU-SILC data 2005–2017 (Austria 2018). Diamonds indicate the raw gender wage gap in Austria in gross hourly wages. Circles indicate the residuals from decompositions of the wage gap ("unexplained component"), using the same set of characteristics in each year, using pooled models

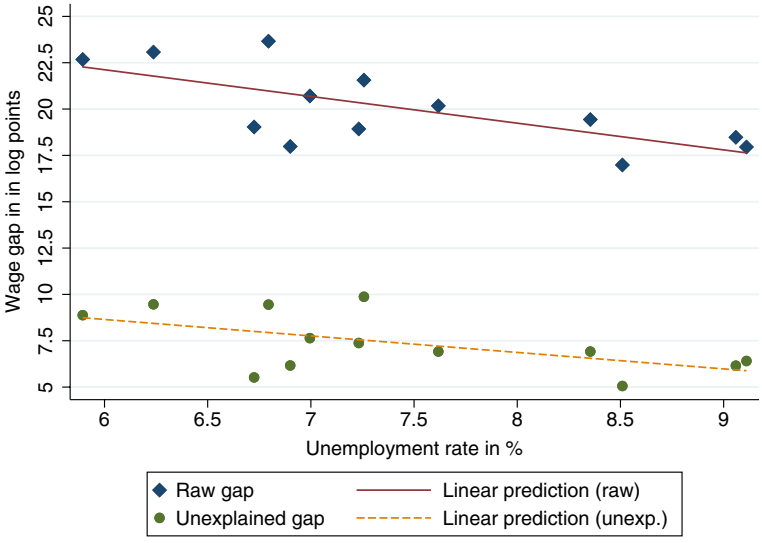


Fig. 6 Gender wage gap and the business cycle, private sector. *Notes*: Austrian EU-SILC data 2005–2017 (Austria 2018). Diamonds indicate the unadjusted gender wage gap in Austria in gross hourly wages. Circles indicated the residuals from decompositions of the wage gap ("unexplained component"), using the same set of characteristics in each year

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