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Gender and Education Gaps in Employment:

New Evidence for the EU

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Abstract

This paper analyses (age-adjusted) employment rates by gender and education. We find that male-female gender gaps and high-low education gaps in employment vary markedly across European Union (EU) countries and regions, with larger gaps existing in Eastern and Southern Europe than in Nordic and Continental EU countries. We estimate that closing existing education gaps in employment between high and lower education levels would raise the employment rate in the EU for the year 2022 by 10.6 percentage points, whereas closing the gender gaps between men and women would lead to an increase of 2.5 percentage points. At the same time, closing both the gender and education gaps would raise the EU employment rate from 76% to 89% of the population. Furthermore, we provide new evidence on the cyclical behaviour of employment gaps, finding that gender gaps are procyclical. While female employment rates tend to be more resilient than male employment rates during economic downturns, male employment rates tend to grow at a faster pace than female employment rates during upswings. In contrast, education gaps are more countercyclical, as employment risks are more strongly concentrated where education is low.

Keywords: Full employment, unemployment, employment gaps, gender, education, EU, business cycle

JEL classification: E24, E32, E6, J63, J64

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1. Introduction

How much would the employment rate of women have to rise in comparison with men to close existing gender gaps in employment? How many people with low education would have to be brought (back) into the labour market to match the employment record of those with high education levels? There is a large amount of literature on different labour market outcomes of men and women on a wide range of issues, such as the impact of having children on the women's wages and employment outcomes (e.g. Kleven et al. 2019; Cukrowska-Torzewska and Matysiak 2020; Tverdostup 2023) or the gender pay gap (e.g. Weichselbaumer and Winter-Ebmer 2005; Blau and Kahn 2017). Similarly, the role of education in labour markets has been studied extensively, such as with regard to its impact on employment and wages (e.g. Card 1999; Lagakos et al. 2018). While different employment trajectories of men vs. women and high- vs. low-education groups are well documented, gender and education gaps in employment remain understudied, especially with regard to how they vary across regions and how they respond to cyclical conditions. Many studies investigate the evolution of (un)employment rates and their drivers over time, especially in a European context (e.g. Mikosch and Sturm 2012; Lechler 2019).

This paper contributes to the literature by providing new estimations of gender and education gaps in employment for the European Union's (EU) member states as well as new findings on whether these employment gaps are linked to cyclical swings in the economy. The respective employment gaps refer to the difference between the employment rate of a particular group and that of a reference group. We use men with a high education level as the benchmark, as this group consistently shows the highest employment rates in historical perspective and is the least likely to suffer from labour market discrimination. To make aggregate groups comparable, we adjust employment rates by accounting for different age distributions across gender and education groups. In so doing, we contribute to studying how far different countries and regions are away from full employment (e.g. Gökten et al. 2024; Council of Economic Advisers 2024) as well as to understanding how cyclical swings in the economy affect important groups in the labour market differently (e.g. Acemoglu and Autor 2011; Gomes 2024).

The rest of the paper is structured as follows. Section 2 discusses the data on employment rates and the age-adjustment methodology that we use to estimate the relevant employment gaps. Section 3 presents stylised facts of gender and education gaps in employment across the EU's member states and regions. Section 4 provides a descriptive analysis of whether cyclical swings in the economy are systematically linked with employment gaps. Section 5 puts forward a multivariate panel regression analysis of whether cyclical conditions affect employment gaps. Section 6 discusses our findings in the context of the existing literature. Section 7 provides a summary and conclusion.

2. Data and methodology

We use data from Eurostat covering both genders, five age groups (15-24, 25-34, 35-44, 45-54 and 55-64), and three education levels: 'high' (ISCED 5-8) refers to individuals with tertiary education, 'medium' (ISCED 3-4) to individuals with upper-secondary or post-secondary non-tertiary education, and 'low' (ISCED 0-2) to individuals with primary or lower-secondary education. We exclude individuals over the age of 65 from our analysis due to limited data availability for this age group in most countries. The dataset comprises employment levels, population numbers and employment rates. Furthermore, we utilise Eurostat data at the NUTS 2 level, which includes the same categories as those listed above.

To present our findings, we categorise EU countries into the five groups proposed by Arts and Gelissen (2002). This classification divides our countries into Anglo-Saxon (Ireland and the UK), Continental (Austria, Belgium, France, Germany, Luxembourg and the Netherlands), Nordic (Denmark, Finland and Sweden), Southern (Cyprus, Greece, Italy, Malta, Portugal and Spain) and Eastern countries (Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia). We compute the aggregated rates for each of these groups by taking the population-weighted arithmetic average of the countries in the respective group.[1]

The employment rate is calculated by dividing the number of employed individuals within a specific age-gender-education group by the total population of that same group. To improve the comparability of different demographic groups, we adjust our employment rates by age. The adjustment accounts for different age distributions across gender and education and allows us to get a clearer picture, as some demographic groups (e.g. those with lower education levels) typically have a higher proportion of younger individuals. The latter are more likely to be in school or to not have entered the labour market yet, which results in lower employment rates. For each group, we perform the adjustment by applying weights to the age groups within each demographic group. The weights are calculated based on the age distribution of the high-educated male population. Overall, age adjustment has a greater impact on employment rates by education compared to gender. This outcome is expected due to the similarity in age distribution among genders, whereas there is a more significant difference in age distribution across education levels. The low- and medium-educated populations have a higher proportion of younger individuals compared to the high-educated population.

Table 1 presents the population-weighted average employment rates for the female and male populations in our sample of countries for 2019. While the first column shows the actual employment rate, the second column shows the age-adjusted rates based on the age distribution of the male population. The age adjustment for females results in a slight decrease in female employment rates on average. This is due to the higher proportion of men than women in younger age groups as well as to the fact that younger individuals tend to have a lower labour market participation rate.

1 However, results are similar when we use simple (unweighted) arithmetic means.

Table 1 / Employment rates by gender, 2019, % of population

Year	Gender	Employment rate	Age-adjusted employment rate
2019	Female	64.39	64.24
2019	Male	74.5	74.5

Source: Eurostat, authors' calculation.

Note: The table displays the population-weighted average rates for our entire sample. Age adjustment is computed based on the age distribution of the male population. Due to data unavailability for Ireland and the UK after 2020, we used the last available year for all regions (i.e. 2019).

Table 2 shows the comparison between the actual employment rate and the age-adjusted employment rate in 2019. The age-adjusted employment rate indicates the employment rate that the low- and medium-educated populations would have if they shared the same age distribution as the high-educated population. The low- and medium-educated groups have a higher proportion of young individuals compared to the high-educated group. Adjusting for age in this context increases the employment rate for the low- and medium-educated groups. This results from the fact that a significant portion of the younger population is either pursuing education or has not entered the labour market yet. For sensitivity checks, we exclude the 15-24 age group to omit youth still in education. Without the age adjustment, the average employment rate (for the 25-64 age group) is 86% for the high-educated, 57% for the low-educated, and 77% for the medium-educated. Age adjustment slightly increases the rates to 60% for the low-educated and 78% for the medium-educated. These results align with the results of our baseline age adjustment, which underlines its importance.

Table 2 / Employment rates by education, 2019, % of population

Year	Education level	Employment rate	Age-adjusted employment rate
2019	Low (ISCED 0-2)	45.99	57.53
2019	Medium (ISCED 3-4)	71.33	76.46
2019	High (ISCED 5-8)	84.84	84.84

Note: The table displays the population-weighted average rates for our entire sample. Age adjustment is computed based on the age distribution of the high-educated male population. Due to data unavailability for Ireland and the UK after 2020, we used the last available year for all regions (i.e. 2019).
Source: Eurostat, authors' calculation.

We define the employment gap as the difference between the employment rate of a particular group and that of a reference group. We aggregate the age-adjusted employment rates by age and calculate the employment gaps annually. As reference groups, we use the male population for the gender gap and the high-educated (ISCED 5-8) population for the education gap. To calculate the potential employment rates after closing the employment gaps, we use the high-educated male population (ISCED 5-8) as our main reference group and calculate the potential employment rate if every demographic group were to have the same employment rate as the high-educated male population. We take this group as our benchmark because it has consistently exhibited the highest employment rates over the past 22 years and is also the group least likely to suffer from labour market discrimination. This selection means that this group also serves as our reference and benchmark for age adjustment.

We use output gap data from AMECO to proxy for the business cycle. Boom periods are characterised by a positive output gap, indicating that actual GDP exceeds potential GDP. In contrast, downturn periods are characterised by a negative output gap, indicating that actual GDP is below potential GDP for a given year. The output gap is defined as the difference between actual and potential GDP at constant market prices, expressed as a percentage of potential GDP. Potential GDP represents the level of GDP that would be achieved if labour and capital were utilised at non-inflationary levels (Havik et al. 2014).

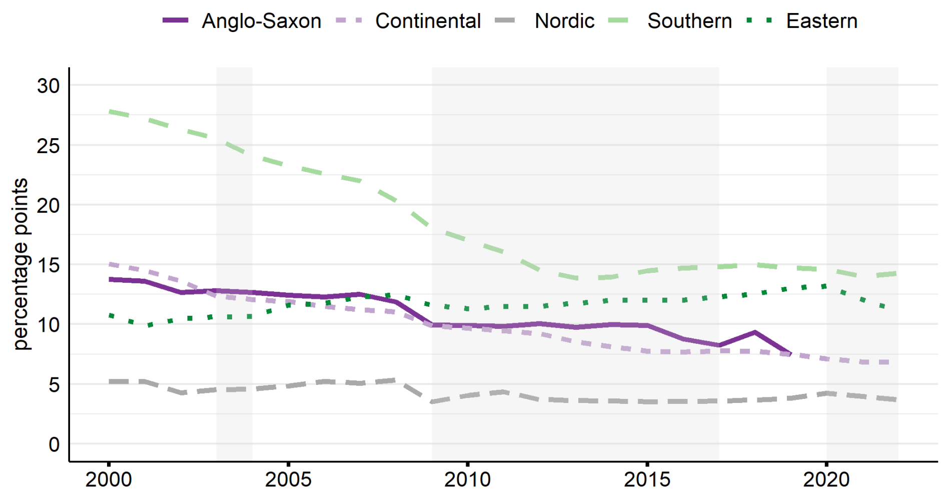
To analyse the relationship between business cycles and employment gaps, we use GDP data from the AMECO database. For visualisation purposes, we group our sample into five categories based on Arts and Gelissen (2002) and aggregate GDP using population weights. In Section 4.1, we will examine the cyclical components of GDP and the employment gaps. To derive these series, we apply the Hodrick-Prescott filter (HP filter) to isolate cyclical variations from the long-term trend in GDP and employment gaps (Hodrick and Prescott 1997). The HP filter consists of an algorithm with a smoothing parameter at its core.[2]

[2] Given arguments about problems associated with using the HP filter, we also apply the Hamilton filter (HM filter), which uses leads and lags of the data points of interest for detrending (Hamilton 2018). In Figure A 2 and A 3 in Appendix A, we present comparisons of HP and Hamilton filters for gender gap and GDP, respectively. The HM filter tends to result in higher volatilities in the trend component, and its trend displays a mean-adjusted, phase-shifted version of the original series. Thus, for the main section, we opted to employ the HP filter.

3. Stylised facts on employment gaps

In 2019, the population-weighted average employment rate for women in our sample was 64.2%, whereas men's rate stood at 74.5%. Despite a decrease in the average employment gap from 16.7 percentage points (pp) in 2000, there is still a gender employment gap of 10.3 percentage points. With the exception of Eastern Europe, the gender gap in employment has generally decreased over time. In Eastern Europe, the gender gap reached its peak at 13.2 percentage points in 2020 (see Figure 1). Despite the fact that more women are participating in the labour force (the female employment rate increased from 53% in 2000 to 65% in 2022), the gender gap in employment in Eastern Europe persists over time (see Figure A 1 in Appendix A).

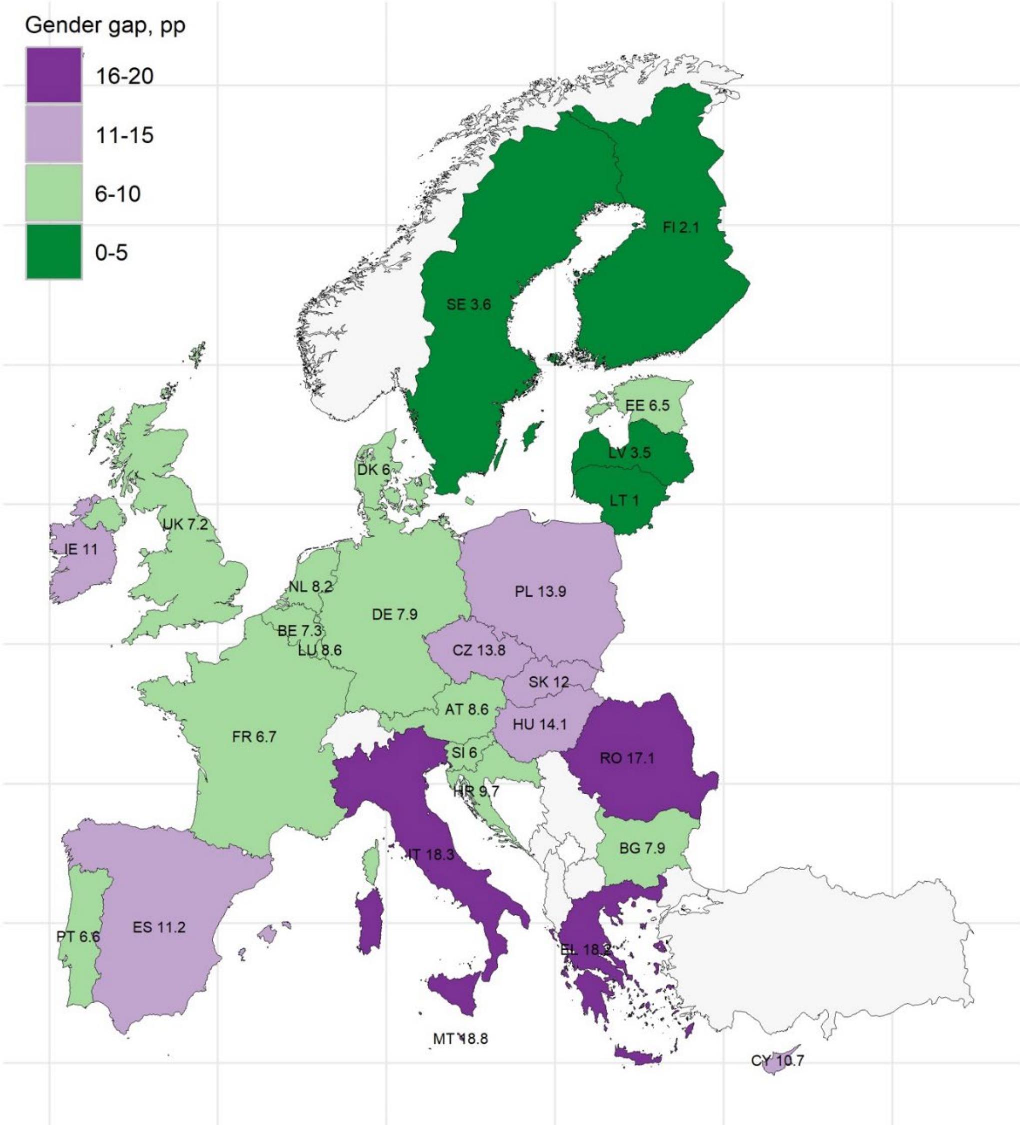
Figure 1 / Gender gap in employment, 2000-2022



Notes: The shaded areas in the figure indicate downturn periods for the EU27, which are characterised by a negative output gap. The gender gap in employment is the difference between male and female employment rates in percentage points. Employment rates are age-adjusted, with the male population serving as the reference group.
Source: Eurostat, authors' calculation.

Figure 2 illustrates the gender gap in employment for individual countries for 2019. Due to data unavailability for the UK and Ireland after 2020, the last available year (i.e. 2019) is shown. The gender gap is defined as the percentage-point difference between male and female employment rates, with the employment rates adjusted for age (as discussed in Section 2). Finland, Sweden, Lithuania and Latvia exhibit the smallest gender gaps (below 5 pp). Italy, Greece and Romania display the largest gender gaps, with over 15 percentage points. The gender gap is slightly larger in Austria than in Germany and the Netherlands (8.6, 7.9 and 8.2 pp, respectively).

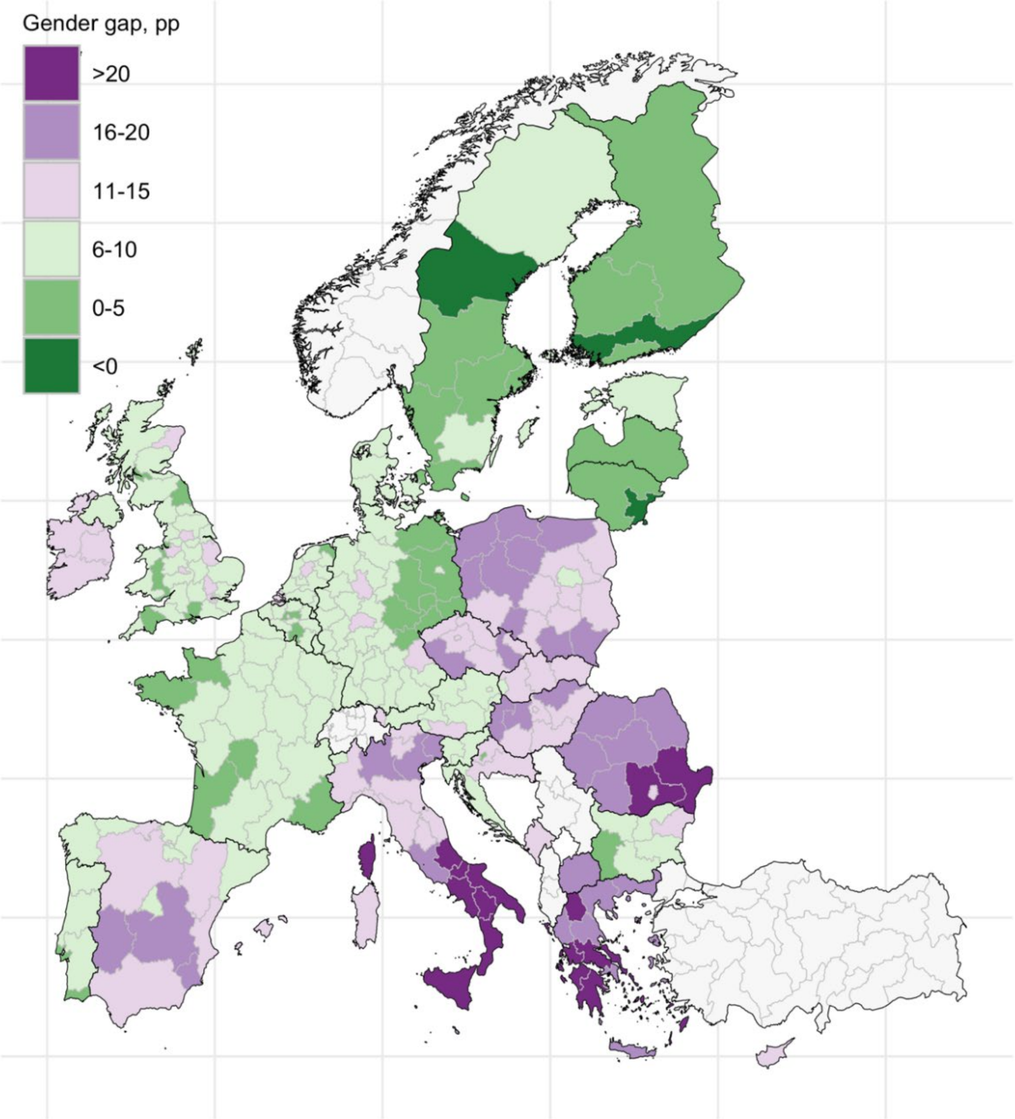
Figure 2 / Gender gap in employment at country level, 2019



Notes: The gender gap in employment is the percentage-point difference between male and female employment rates within a country in 2019. Employment rates are age-adjusted.
Source: Eurostat, authors' calculation.

In a next step, we ask whether the gender gap also varies across regions (see, e.g., Lechler 2019 on regional employment variation). The gender gap in employment across EU NUTS 2 regions (see Figure 3) does indeed show significant variation, with regions in Greece, Italy and Romania showing the largest gaps in employment, while Scandinavian and Baltic regions demonstrate the smallest gender gaps. In 2019, there were 17 NUTS 2 regions in which the gender gap was at least 20 percentage points. Most of these regions were in Italy and Greece, with seven regions in Italy and six regions in Greece, while the remaining three regions were in Romania (2) and France (1). There are also notable disparities within countries. In Greece and Italy, southern regions tend to have larger gender employment gaps than northern regions. In other countries, gender gaps are only below the EU average in capital regions, while the gaps are significantly larger in other regions. One notable example is Poland, where only the Warsaw metropolitan area displays a gender employment gap of below 10 percentage points. Similarly, in Romania, the gender gap in employment in the metropolitan region around Bucharest is only half the gap found in other regions (11 vs. 20 pp).

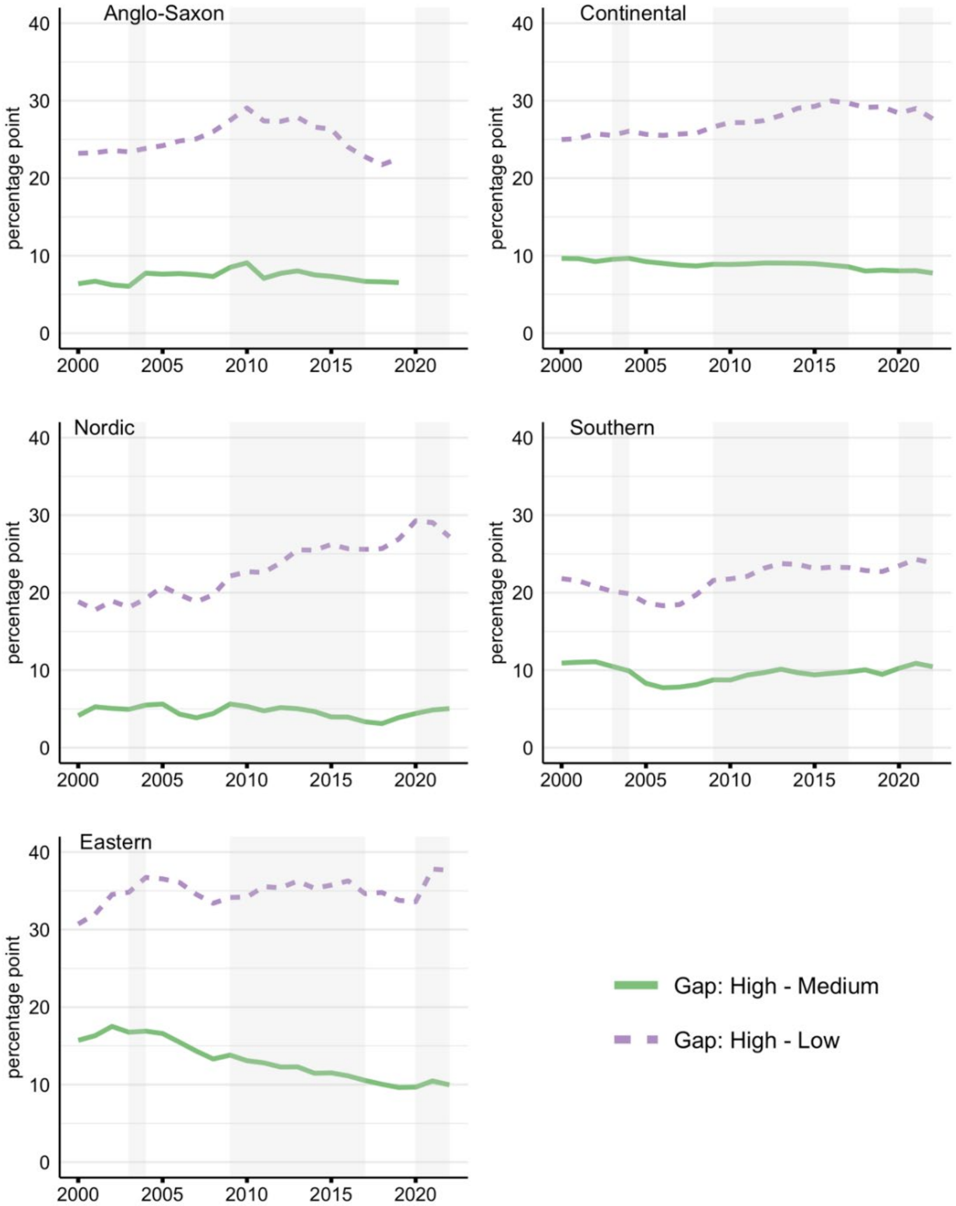
Figure 3 / Gender gap in employment at NUTS 2 level, 2019



Notes: Due to data limitations at NUTS 2 level, the employment gap is not adjusted for age. The gender gap in employment is the percentage-point difference between male and female employment rates within a NUTS 2 region in 2019.
Source: Eurostat, authors' calculation.

In all regions, we observe a larger employment gap between high- and low-educated individuals than between high- and medium-educated individuals. Across regions, the gap between high- and low-educated individuals has widened over the period from 2000 to 2022, except in the Anglo-Saxon countries (see Figure 4).

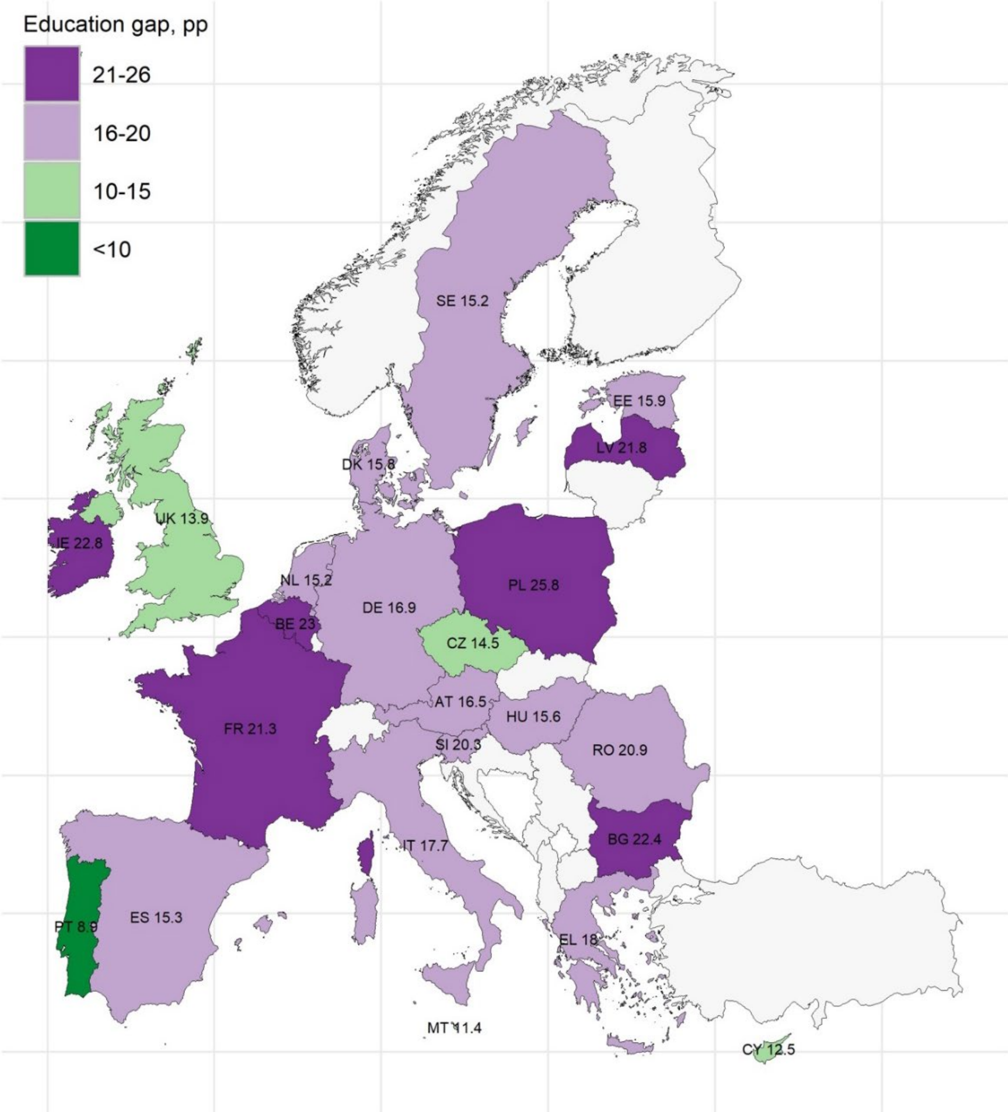
Figure 4 / Education gap in employment, 2000-2022



Notes: The shaded areas in the figure indicate bust periods for the EU27, which are characterised by a negative output gap. The education gap in employment is the difference in employment rates between the highly educated and those with low education in percentage points. Employment rates are age-adjusted, with the highly educated population serving as the reference group.
Source: Eurostat, authors' calculation.

Figure 5 shows the average education gap in employment across our sample countries for 2019. The average education gap is calculated as the arithmetic average of the employment gaps between high-medium and high-low educated individuals, adjusted for age. Due to insufficient data on education breakdown by age for certain countries, observations from Croatia, Finland, Lithuania, Luxembourg and Slovakia are excluded. Education gaps are significantly larger than gender gaps, ranging from 8.9 percentage points in Portugal to 25.8 percentage points in Poland. Unlike for the gender gaps, we do not observe a consistent regional pattern for the education gaps. Poland exhibits the largest average education gap, followed by Belgium, Ireland, Bulgaria, Latvia and France. The smallest average education gap is observed in Portugal, followed by Malta, Cyprus, the UK and Czechia. Austria's education gap (16.5 pp) is in the middle of the range.

Figure 5 / Average education gap in employment at country level, 2019

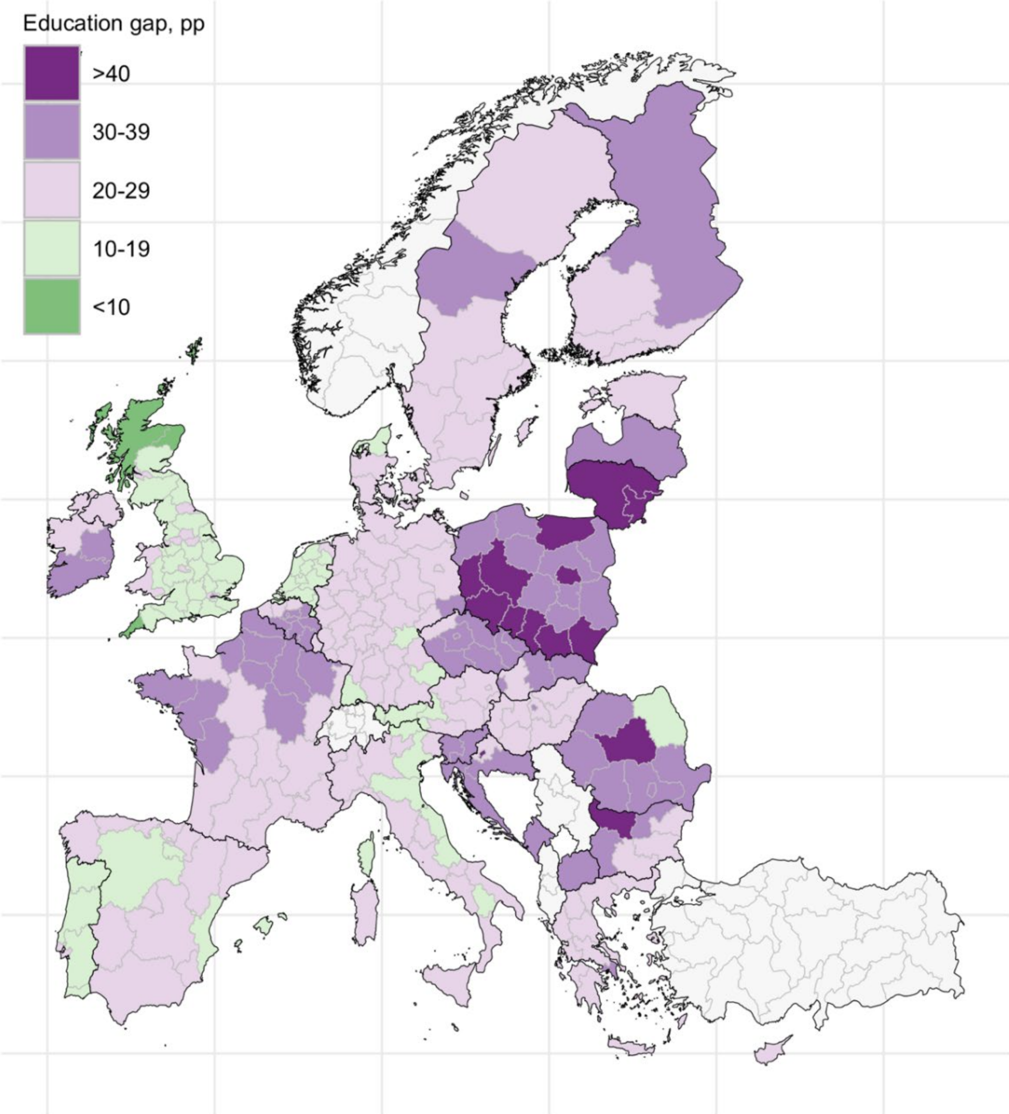


Notes: The average education gap is calculated as the mean of the employment gaps between individuals with high and low education levels and between individuals with high and medium education levels. Due to data limitations regarding education levels, we excluded observations from Croatia, Finland, Lithuania, Luxembourg and Slovakia.
Source: Eurostat, authors' calculation.

Figure 6 displays the average education gaps across NUTS 2 regions for 2019. Due to data limitations, we utilise Eurostat's NUTS 2-level employment rates broken down by education level. As the age breakdown for the data is insufficient for age adjustment, we show unadjusted education gaps in the figure. As noted earlier, in comparison to gender gaps, subregional average education gaps are significantly larger, ranging from 7.9 to 46 percentage points. At the NUTS 2 level, we observe quite consistent regional patterns, with the highest education gaps being concentrated in Eastern Europe.

There are 14 NUTS 2 regions in which the average education gap in employment exceeds 40 percentage points, with nine regions in Poland, two in Lithuania, and one each in Bulgaria, Croatia and Romania.

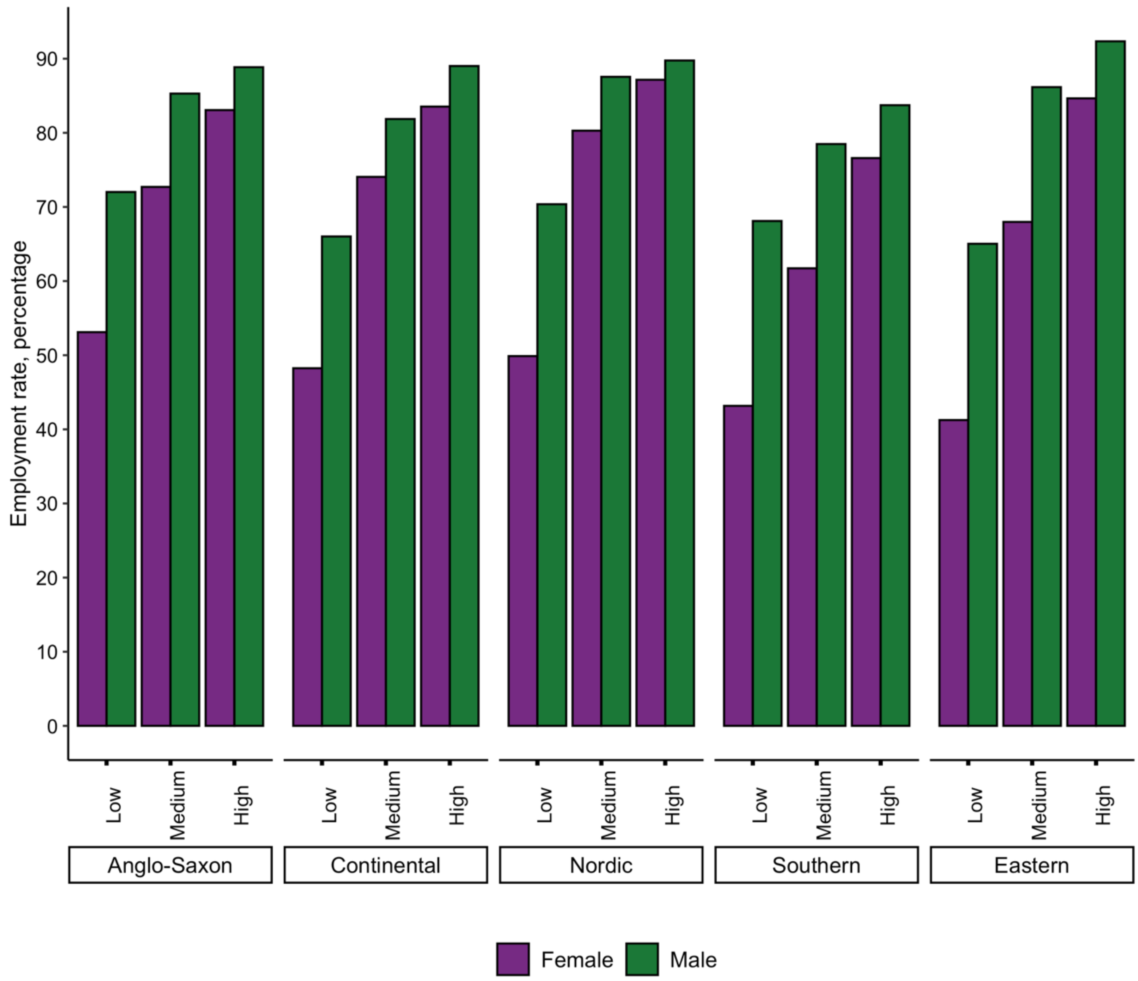
Figure 6 / Average education gap in employment at NUTS 2 level, 2019



Notes: The average education gap is calculated as the mean of the employment gaps between individuals with high and low education levels and between individuals with high and medium education levels. Due to data limitations at the NUTS 2 level, the employment gap is not adjusted for age.
Source: Eurostat, authors' calculation.

In all regions, women with low levels of education suffer a double disadvantage. Although gender employment gaps persist across all levels of education, they tend to be largest among those with low levels of education (see Figure 7). On average across regions, there is an (age-adjusted) employment gap of 21.2 percentage points between low-educated males and females, with the highest disparity being observed in Southern regions (24.9 pp) and the lowest in the Continental regions (17.8 pp). In comparison, the employment gap is notably smaller in the medium-educated populations, averaging 12.5 percentage points across all regions. The Eastern region exhibits the largest gender gap in employment among those with low education (18.2 pp), while the Nordic region shows the smallest gap (7.3 pp). Among the highly educated population, the employment gap is the smallest, averaging 5.7 percentage points across the regions. The Eastern regions also exhibit the largest gender employment gap for the high-education group (7.7 pp), while the Nordic region shows the smallest employment gap (2.6 pp). In Eastern regions, highly educated females surpass males in educational attainment. There is a 15 percentage-point difference between the high-educated female and male populations, which is the largest observed in our sample. However, despite this fact, the gender gap in employment for the highly educated population in the Eastern regions is also the largest in our sample.

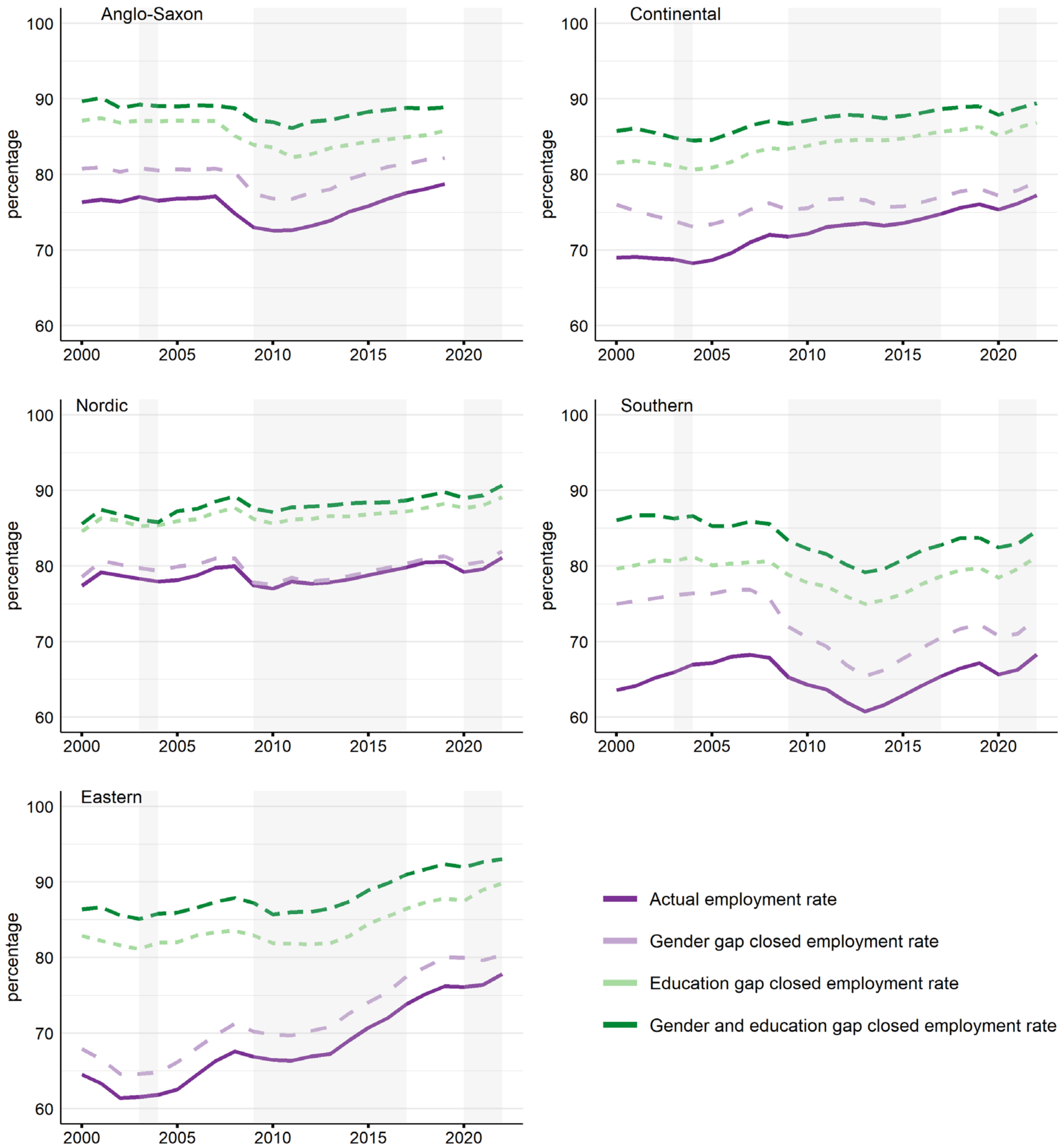
Figure 7 / Employment rates by education and gender, 2019, % of population



Notes: Employment rates are age-adjusted, using highly educated males as the reference group. Due to data unavailability for Ireland and the UK after 2020, we used the most recent year for which data are available for all regions (i.e. 2019).
Source: Eurostat, authors' calculation.

Figure 8 shows our estimation of potential employment rates after closing employment gaps in gender and education. By closing employment gaps, all demographic groups attain the same employment rate as high-educated males. To calculate the potential employment rates, we first close the gender gap by aligning female employment rates with corresponding male employment rates in each education category. We then similarly close the education gap by adjusting the employment rates of low- and medium-educated individuals with those having high education. Over the sample period, closing the education gap in employment has the most significant impact on the employment rate across regions, with an average increase of 11.6 percentage points in the employment rate, whereas closing the gender gap results in a 3.8 percentage-point increase.

Figure 8 / Potential employment rates, 2000-2022



Notes: The shaded areas in the figure indicate downswing periods for the EU27, which are characterised by a negative output gap. Employment rates are age-adjusted, with highly educated males serving as the reference group.
Source: Eurostat, authors' calculation.

Specifically, closing the gender gap has the highest impact in the Southern region, increasing the employment rate by almost seven percentage points. This is followed by the Anglo-Saxon region, with an increase of four percentage points, the Continental region, with an increase of 3.6 percentage points, and the Western region, with an increase of 3.4 percentage points. The Nordic region shows the least impact, with an increase of only 0.9 percentage points.

In contrast, closing the education gap has the highest impact in the Eastern region, with a 15.6 percentage-point increase in the employment rate, followed by the Southern region, with a 13.7 percentage-point increase, the Continental region, with an 11.4 percentage-point increase, and the Anglo-Saxon region, with a 9.5 percentage-point increase. Once again, the Nordic region experiences the least impact, with an eight percentage-point increase over the sample period.

Ultimately, closing both the gender and education gaps has the most significant impact on the Eastern region, with an almost 20 percentage-point increase in the employment rate, followed by an increase of 18 percentage points in the Southern region, 15 percentage points in the Continental region, 13 percentage points in the Anglo-Saxon region, and nine percentage points in the Nordic region.

Over time, the impact of closing both the gender and education gaps on employment rates has slightly diminished as these gaps have gradually narrowed. In 2000, closing both gaps would have resulted in an average employment-rate increase in the EU of 16.5 percentage points across all regions. By 2022, this impact was lower, at 13.1 percentage points.

4. A statistical filtering approach on whether gender and education gaps in employment move with the business cycle

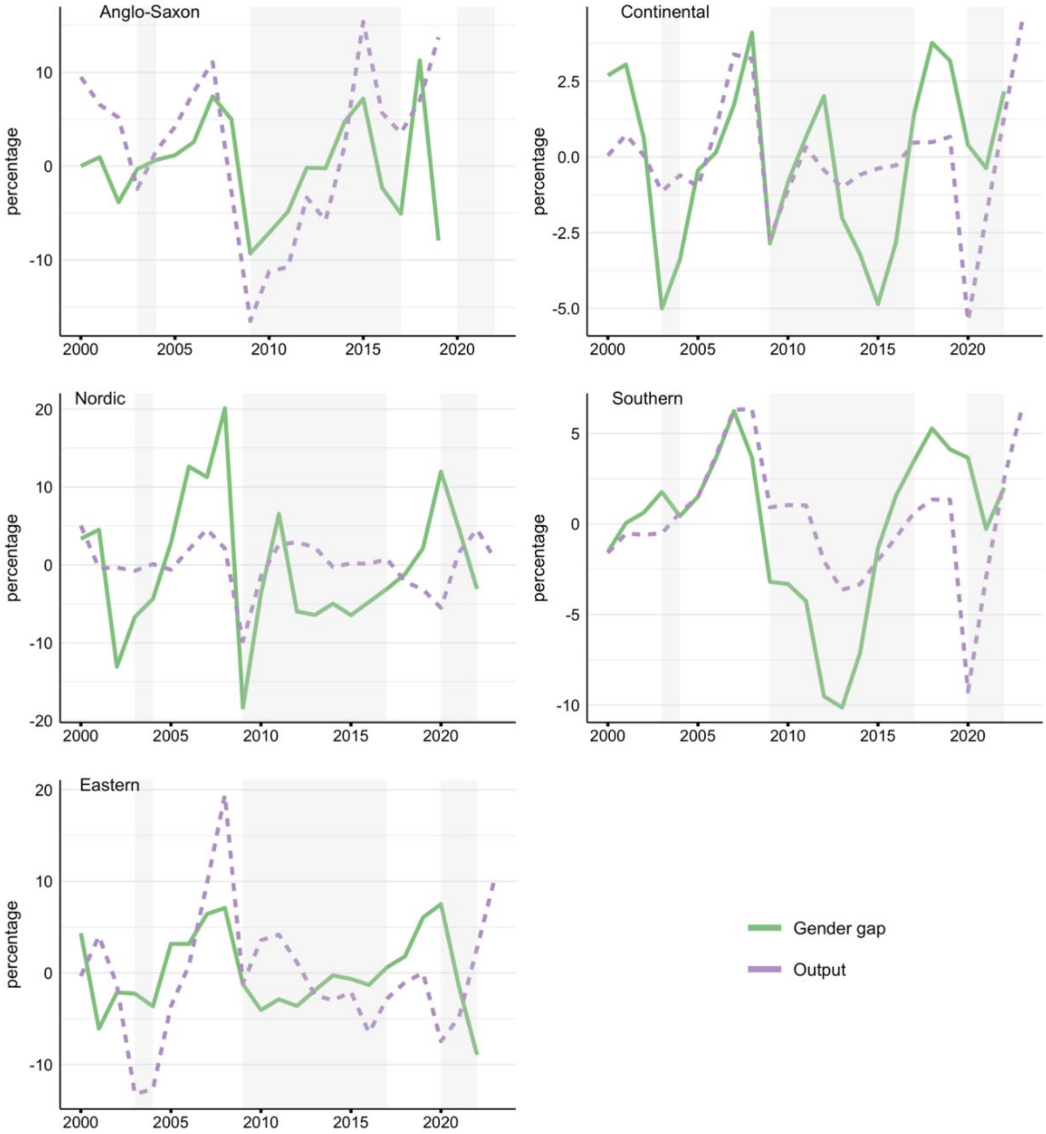
The main focus of this section is to investigate how gender and education gaps in employment move with the business cycle. This is relevant for understanding whether running the economy hot will, overall, contribute to closing the relevant employment gaps (e.g. Sigl-Glöckner et al. 2021).

The existing econometric literature focuses on the output gap as the preferred measure of the business cycle. The output gap is defined as the difference between actual and potential output (typically expressed as percentage of potential output), where the latter represents what the economy should be able to produce in the absence of higher inflationary pressures (e.g. Havik et al. 2014). Potential output is routinely estimated by using statistical filtering methods (e.g. Coibion et al. 2018; Heimberger et al. 2020), where the trend component of actual output excludes the cyclical component of GDP and is interpreted as potential output. Potential output, as derived from the distinction between trend and cycle in the GDP time series, can then be used to express the output gap as the percentage deviation of actual from potential output. In this subsection, we follow this statistical filtering approach to estimate deviations of actual gender and education gaps in employment from their trend. We use the Hodrick-Prescott (HP) filter to distinguish trend and cycle, as explained in Section 2.

Figure 9, which is based on using the HP filter, provides a descriptive analysis of whether deviations of actual gender rates from the trend systematically move with the business cycle, measured in terms of output deviations from the trend. The deviation from the trend in percentage terms is calculated by dividing the cyclical component (i.e. original series minus trend) by the trend. We distinguish the five EU country groups introduced in Section 2.

The descriptive analysis suggests that gender gaps move procyclically. In other words, an improvement in the business cycle, signalled by an upward move in the output gap, typically coincides with an increase in the gender gap, although this is not always the case. In particular, the data for the Anglo-Saxon, Nordic and Eastern country groups show that gender gaps in employment declined (i.e. moved countercyclically) during the COVID-19 pandemic. However, for previous years, there seems to be a broad pattern of a decline in gender gaps in employment during downswings and an increase in gender gaps during upswings, which points to procyclicality. This suggests that female employment rates tend to be more resilient than male employment rates during economic downturns, leading to a decrease in the gender gap, whereas male employment rates grow at a faster pace during economic upswings, resulting in an increase in the gender gap in employment. Existing evidence suggests that women's employment outcomes are significantly less exposed to cyclical conditions than men's (Gomes 2024).

Figure 9 / Output and gender gap, deviation from trend, HP filter, 2000-2022



Notes: The shaded areas in the figure indicate bust periods for the EU27, which are characterised by a negative output gap. Employment rates are age-adjusted, with the male population serving as the reference group.
Source: Eurostat, authors' calculation.

The distribution of employment across sectors provides insights relevant for understanding the evolution of gender gaps. Table 3 presents the female share and female employment rates across NACE 2-digit sectors in the EU in 2019. The female share is calculated as the ratio of female employees in each sector to the total sector employment, and the figure for female employment is the ratio of female employees in each sector to the total number of female employees. The table shows that there is a clear gender disparity in employment across sectors. Male employees outnumber females in industries such as 'manufacturing' (Sector C) and 'construction' (Sector F), while female employees are more likely to work in services sectors. Specifically, women are heavily concentrated in sectors like 'education' (Sector P) and 'health care' (Sector Q), where they account for more than 70% of the workforce. A similar pattern is also evident in the distribution of females across sectors. The largest portion of females is employed in the 'health and social work activities' sector (Sector Q), accounting for 18.4% of female employment. This is followed by the 'wholesale and retail trade' sector (Sector G), with 14.8%, and the 'education' sector (Sector P), with 11.5%.

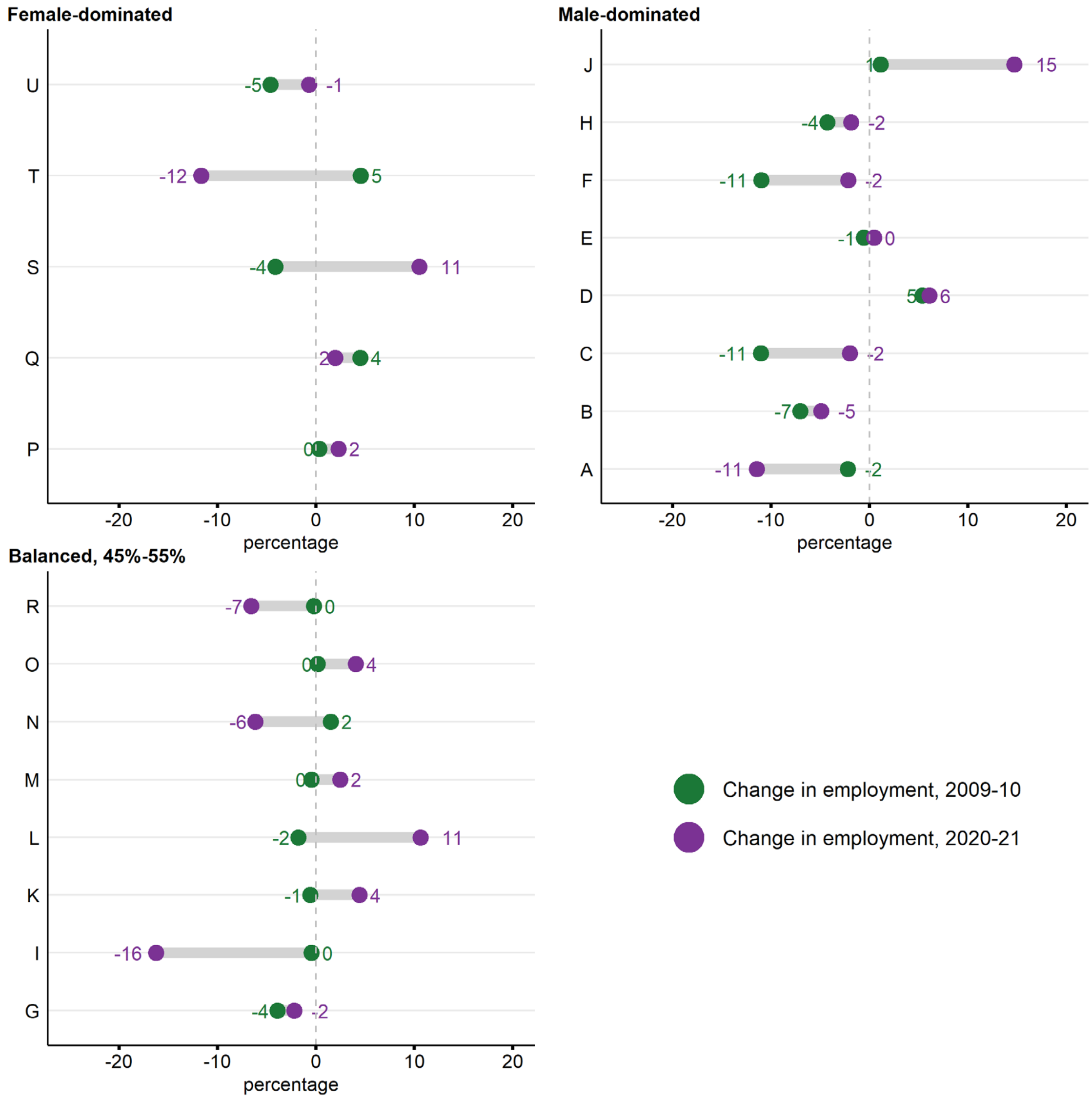
Table 3 / Share of female and male employees, percentage, EU27, 2019

Sector	Female share, %	Female Employment, %
A - Agriculture, forestry and fishing	33.3	2.9
B - Mining and quarrying	13.1	0.1
C - Manufacturing	30.1	10.8
D - Electricity, gas, steam and air-conditioning supply	25.1	0.4
E - Water supply, sewerage, waste management and remediation	21.7	0.4
F - Construction	9.6	1.4
G - Wholesale and retail trade	49	14.8
H - Transportation and storage	22.5	2.6
I - Accommodation and food service	54	5.6
J - Information and communication	30.3	2.1
K - Financial and insurance activities	53	3.1
L - Real estate activities	52	0.8
M - Professional, scientific and technical activities	49.3	5.9
N - Administrative and support service activities	49.1	4.4
O - Public administration and defence	48	7.2
P - Education	72.6	11.5
Q - Health and social work activities	78.6	18.4
R - Arts, entertainment and recreation	48.5	1.7
S - Other services	67.3	3.5
T - Activities of households as employers	88.9	2.1
U- Activities of extra-territorial organisations and bodies	54.2	0.1

Notes: Female employment is calculated by dividing the number of females in each sector by the total employed females. Female share is determined by dividing the number of females in each sector by the total individuals employed in that sector.
Source: Eurostat, authors' calculation.

Male-dominated industry and female-dominated services sectors have historically responded to business cycles in different ways. Specifically, during recessions, employment in industries tends to exhibit greater drops compared to the services sectors. Table A 1 in Appendix A shows the sectoral change in employment levels broken down by gender. During the global financial crisis (GFC), the largest decrease in employment was observed in sectors such as 'agriculture' (Sector A); 'manufacturing' (Sector C); 'professional, scientific and technical activities' (Sector M); 'administrative and support service activities' (Sector N); and 'arts, entertainment and recreation' (Sector R). Except for 'manufacturing' sector (Sector C), drops in male employment levels were larger than those in female employment levels. In contrast, during the COVID-19 pandemic, the most significant decreases in employment were observed in the following sectors: 'transportation and storage' (Sector H); 'accommodation and food service' (Sector I); 'administrative and support service activities' (Sector N); and 'arts, entertainment and recreation' (Sector R). The change in employment in these sectors was either even for both genders or, as seen in the 'accommodation and food service' sector (Sector I), the decrease was larger for female employees.

Figure 10 / Employment-rate changes by sector and gender during recessions, EU27, %



Notes: Female-dominated sectors are those in which women constitute more than 45% of all employees. In contrast, male-dominated sectors indicate the sectors in which males make up more than 45% of all employees. Balanced sectors have a female share of between 45% and 55%. See Table 3 (above) for a description of sectors A-U.
Source: Eurostat, authors' calculation.

Figure 10 illustrates the sectoral employment change during the 2009-2010 and 2020-2021 periods categorised by the female share in each sector.[3] In sectors predominantly occupied by women, with the exception of Sector T ('activities of households as employers'), there is no notable difference in employment-rate changes. Generally, the most significant decreases in employment rates during recessions occur in sectors dominated by males or those with a balanced gender composition. This trend contributed to the narrowing of the gender gap during recessions. The gender gap widens during

[3] The change in the sectoral employment rate for the periods of 2009-2010 and 2020-2021 is calculated as the difference between the end-of-year employment rate in 2008 and 2010 as well as between 2019 and 2021. We select these periods (end of 2008 and 2019) because they coincide with peaks in employment rates around recessions. This also indicates a lagged reaction of employment to changes in output.

economic upswings as previously laid-off male workers return to employment. In the EU27, for every female employee laid off during bust periods (i.e. those with negative output gaps, as described in Section 2) an average of 3.7 male employees were laid off, while 3.9 male employees were hired for every female employee hired during boom periods (i.e. those with positive output gaps). The difference is more significant in male-dominated sectors, such as manufacturing. In these sectors, for every female employee laid off during bust periods, 1.6 male employees were laid off. However, during boom periods, 7.2 male employees were hired for every female employee hired. This explains the procyclicality of the gender gaps in employment.

We also observe different patterns between the periods of the COVID-19 pandemic and the GFC. During the COVID-19 pandemic, the services sectors were disproportionally affected compared to industry due to their high-physical-contact nature. As expected, the most significant decline in employment during the COVID-19 pandemic occurred in Sector I (‘accommodation and food service’), with a 16% decrease, whereas employment in this sector did not decrease at all during the GFC. Similarly, the ‘agricultural’ sector (Sector A), experienced a 11% decline during the pandemic, whereas it was only impacted to a limited extent during the 2008-2010 period (2%). This is consistent with existing evidence showing that while recent recessions (e.g. the GFC) typically hit male employment more than female employment, the pandemic led to larger employment declines among women in most countries (Alon et al. 2021; Albanesi and Kim 2021; Bluedorn et al. 2021).

Figure 11 shows how education gaps (high-low) in employment move with output gaps. The descriptive analysis suggests that education gaps typically move more countercyclically compared to gender gaps. In other words, as the output gap increases (indicating an improvement in the business cycle), education gaps decline – and vice versa.

Similar to Figure 10, Figure 12 shows sectoral employment changes during the 2009-2010 and 2020-2021 periods in the EU27, but in this case they are categorised by the share of low-educated workers in each sector[4]. The ‘agriculture’ (Sector A) and ‘activities of households as employers’ (Sector T) sectors were the only ones for which the share of low-educated workers exceeded 40%. The majority of sectors have a share of low-educated workers that is below 20%.[5] Similar to gender employment dynamics, significant differences in employment changes are observed between the COVID-19 pandemic and the GFC. This dynamic can help to explain why the countercyclical pattern of education gaps was not present in several regions during the COVID-19 pandemic. During the pandemic, the largest drops in employment occurred in sectors with a high (A, T) or medium (I) concentration of low-educated workers, whereas unemployment risks are typically higher where the average level of education is lower.

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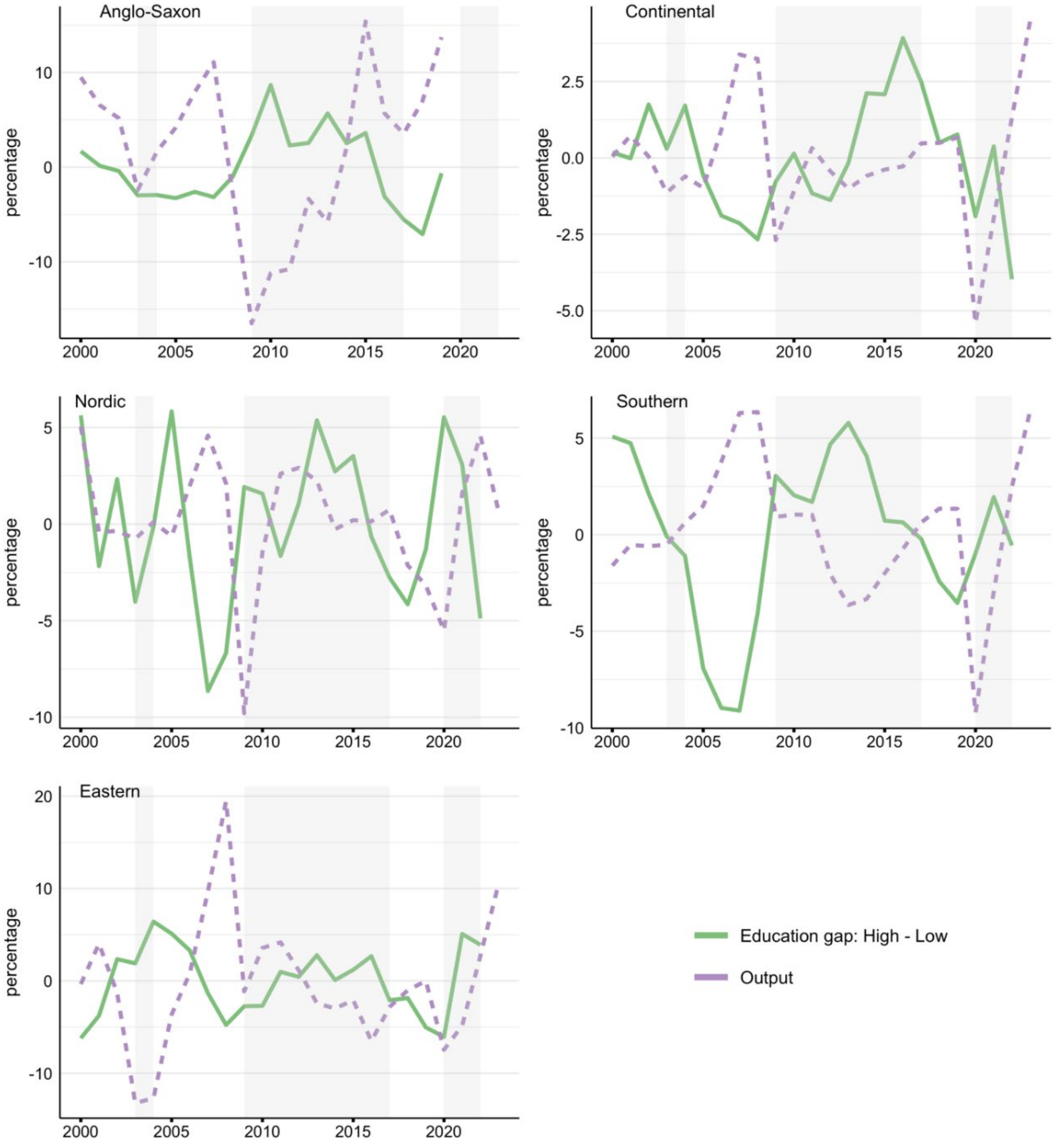
4 Due to data limitations at NACE-2 level for education, we could not provide a similarly detailed analysis of employment rate changes by education level as we did for gender at the NACE-2 level.

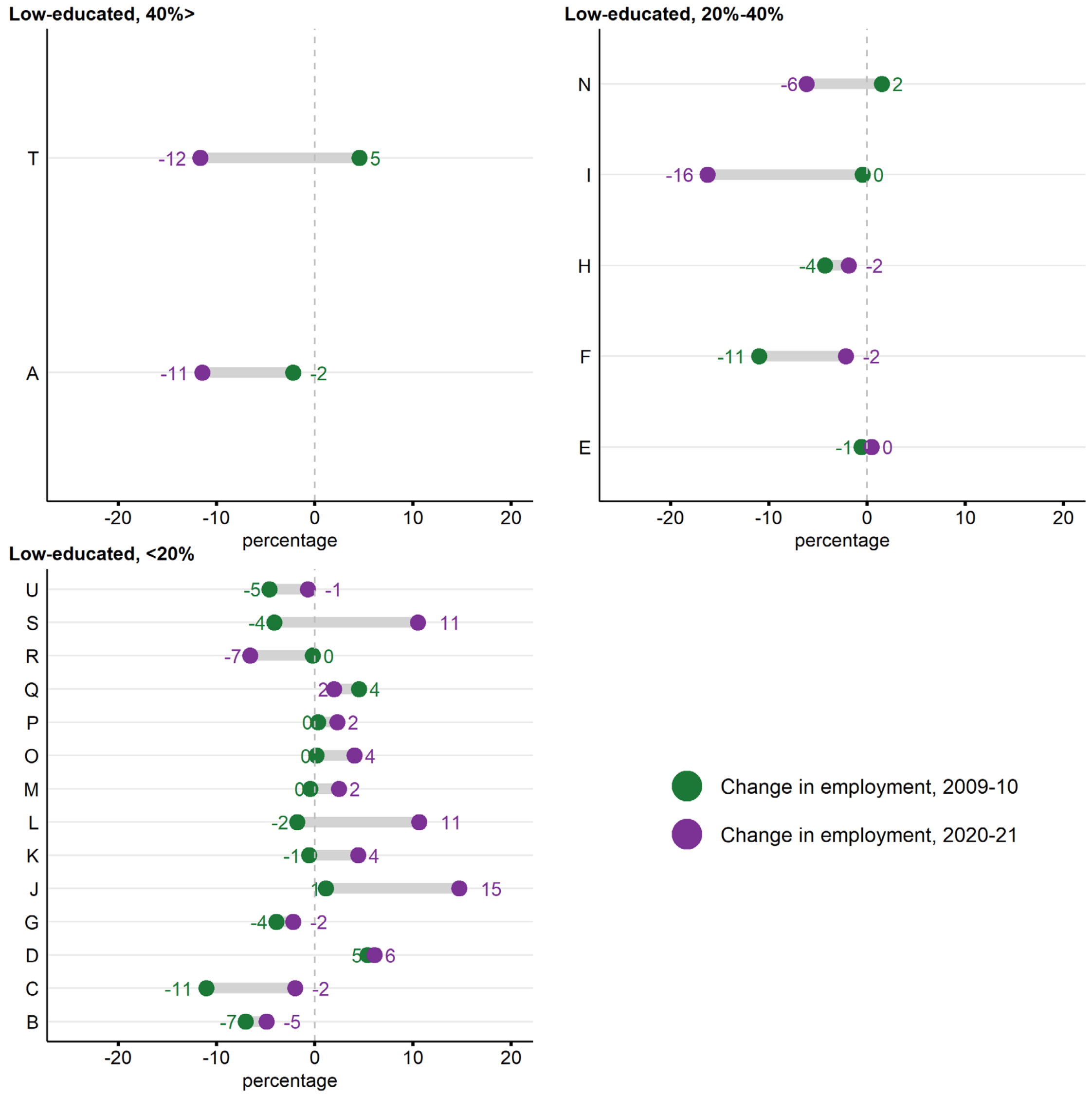
5 Between 2000 and 2022, the share of low-educated workers declined across all sectors, with rates ranging from -0.24% in ‘agriculture’ (Sector A) to - 0.72% in ‘activities of extra-territorial organisations and bodies’ (Sector U). This trend suggests a shift in the workforce dynamics in the EU, which possibly indicates reduced demand for low-skilled labour, increased workforce educational attainment, or both.

Figure 11 / Output and education gap (high-low), deviation from trend, HP filter, 2000-2022, %



Notes: Employment rates are age-adjusted, with the highly educated population serving as the reference group.
Source: Eurostat, authors' calculation.

Figure 12 / Employment rate changes by sector and share of low-educated workers, EU27, %



Notes: The figure categorises sectors by the share of low-educated individuals. Sectors are grouped as follows: over 40% low-educated, 20-40% low-educated, and under 20% low-educated. See Table 3 for descriptions of sectors A-U.
Source: Eurostat, authors' calculation.

5. Multivariate panel regression approach

To investigate in more depth whether gender and education gaps in employment are systematically linked to cyclical fluctuations in the economy, we use a panel regression approach with the following baseline econometric model:

$$EGAP_{i,t} = \alpha + \beta\, C_{i,t} + \gamma\, X_{i,t} + \zeta_i + \xi_t + \varepsilon_{i,t} \quad (1)$$

Here, $EGAP_{i,t}$ is the employment gap related to gender or education, estimated as the difference between actual employment rates and full-employment-consistent employment rates in country *i* at time *t* (see Section 3). $C_{i,t}$ is the cycle variable of interest. While our preferred cycle variable is the output gap, we also provide results that use real GDP growth and the unemployment rate, respectively. $X_{i,t}$ is a vector with additional control variables, which we include to test whether omitted variables have an impact on the estimated cyclicality of the employment gap. The additional controls include variables capturing labour market institutions, macroeconomic development and population as well as macroeconomic variables. ζ_i refers to country-fixed effects, which we include to account for unmeasurable, time-invariant country-specific characteristics.[6] ξ_t represents time-fixed effects, which capture time-varying shocks that hit all countries. And $\varepsilon_{i,t}$ represents the error term.

Table A 2 in Appendix B presents detailed definitions and data sources, and descriptive statistics of the variables are included in Table A 3. Notably, data limitations imply that we can only cover the 2000-2019 period (i.e. the years of the Covid-19 crisis are not part of the analysis). We ran pre-analysis tests, including unit root tests and checks for multicollinearity. Overall, our pre-analysis suggests that our estimation approach is valid. Pre-analysis test results are reported in Appendix B (see Tables A 5-A 7).

Table 4 shows the regression results with the gender gap as the dependent variable of interest. The results suggest that the variables are cointegrated. Column (1) is based on a specification with country- and time-fixed effects, with the output gap representing the cycle as our primary control variable of interest. Column (2) additionally controls for several factors related to labour market institutions (employment protection legislation, union density), structural factors (TFP growth, economic globalisation, age-dependency ratio, fertility rate), macroeconomic factors (real wage growth) and political factors (left-right dimension of government). We control for these variables to test whether the results on the cyclical variable of interest are robust to controlling for a wide range of confounding factors. We find that the output gap in columns (1) and (2) is positively signed and statistically significant at the 95% confidence level. This suggests that gender gaps actually do move procyclically in support of the descriptive results presented in Section 4.1. More specifically, a one percentage-point increase in the output gap, which signals a cyclical improvement in the economy, is related to a 0.45 percentage-point increase in the gender gap in employment in column (1). Both model (1) and (2) explain more than 85% of the variation in the gender gap.

6 Note that our analysis here focuses on the country level and not on the regional level, as was the case in Section 3. The reason for this is that all the data for our explanatory variables were only available at the country level.

Since the output gap is not a perfect measure of cyclical conditions (e.g. Heimberger and Kapeller 2017; Fatas 2019), we assess the robustness of our findings by using different variables that (partly) capture cyclical swings. Columns (3) and (4) show the results with real GDP growth as the cyclical variable of interest, and columns (5) and (6) use the unemployment rate (instead of the output gap). The results consistently suggest that gender gaps are, on average, procyclical. In other words, higher real GDP growth is related to higher gender gaps (and vice versa), and a higher unemployment rate is related to lower gender gaps.

We also run the multivariate panel regression analysis by using the education gap in employment as our dependent variable of interest (see Table 5). The results are strikingly different from those regarding the gender gap. As shown in columns (1) and (2) of Table 5, the sign of the output gap is now negative instead of positive, suggesting that education gaps are countercyclical. The finding of countercyclicality is also supported in the other columns, where we use real GDP growth and unemployment as alternative cyclical variables.

Table 4 / Regression results with gender gap as the dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
Output gap	0.447**	0.401**				
	(0.201)	(0.164)				
Real GDP growth			0.120	0.693**		
			(0.119)	(0.247)		
Unemployment rate					-0.472***	-0.490***
					(0.104)	(0.128)
Employment protection legislation		-0.364		0.700		-1.170
		(1.432)		(1.112)		(1.692)
Union density		-0.515***		-0.509***		-0.525**
		(0.159)		(0.174)		(0.191)
TFP growth		-0.203***		-0.767**		-0.065
		(0.066)		(0.265)		(0.061)
Economic globalisation		-0.105		-0.063		0.253
		(0.189)		(0.168)		(0.216)
Age-dependency ratio		0.040		-0.059		-0.132
		(0.265)		(0.247)		(0.208)
Fertility rate		4.290**		6.334**		-1.216
		(1.830)		(2.363)		(2.944)
Real wage growth		-0.054		0.118		-0.087
		(0.178)		(0.155)		(0.154)
Left-right dimension of government		0.013		-0.115		0.064
		(0.119)		(0.141)		(0.113)
Constant	15.191***	35.211	15.521***	29.642	18.839***	27.005
	(0.320)	(21.714)	(0.375)	(17.179)	(0.646)	(17.456)
Observations	204	204	204	204	204	204
R^2	0.887	0.916	0.863	0.913	0.900	0.924
Adjusted R^2	0.862	0.893	0.833	0.889	0.877	0.902

Table 5 / Regression results with education gap (high-low) as the dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
Output gap	-0.213	-0.290**				
	(0.137)	(0.124)				
Real GDP growth			-0.033	-0.459**		
			(0.092)	(0.181)		
Unemployment rate					0.243**	0.332***
					(0.092)	(0.101)
Employment protection legislation		4.622***		3.848***		5.115***
		(1.390)		(1.280)		(1.555)
Trade union density		-0.076		-0.069		-0.061
		(0.159)		(0.166)		(0.160)
TFP growth		0.152		0.518**		0.053
		(0.097)		(0.235)		(0.070)
Economic globalisation		0.231		0.202		-0.012
		(0.199)		(0.211)		(0.237)
Age-dependency ratio		-0.318**		-0.243*		-0.195
		(0.138)		(0.121)		(0.113)
Fertility rate		-10.228***		-11.534***		-6.466
		(3.376)		(3.836)		(3.944)
Real wage growth		-0.141		-0.263*		-0.125
		(0.116)		(0.134)		(0.112)
Left-right dimension of government		-0.020		0.075		-0.047
		(0.136)		(0.128)		(0.129)
Constant	23.881***	25.594	23.648***	28.732*	22.031***	30.732*
	(0.218)	(14.868)	(0.291)	(14.689)	(0.572)	(17.165)
Observations	204	204	204	204	204	204
R^2	0.913	0.936	0.908	0.933	0.917	0.938
Adjusted R^2	0.894	0.917	0.888	0.914	0.898	0.920

6. Discussion

Our findings add to at least three different strands of literature. First, there is the literature that focuses on conceptualising and measuring deviations from full employment (e.g. Gökten et al. 2024; Fatas 2021; Michaillat and Saez 2022; Lichtenberger et al. 2024). Our paper contributes a new full-employment perspective for EU countries to this literature, as we use men with a high education level as the benchmark and provide estimates on the thought experiment of how much (age-adjusted) employment rates of women and lower-education groups would have to rise to meet this benchmark. In this respect, our approach is most closely related to Mason et al. (2021), who explore alternative measures for potential employment in the US and estimate how many people from different labour market groups could be drawn into employment if US labour markets continued to be tight. They show that socially disadvantaged groups (especially in terms of race) benefit most from tight labour markets given that labour market institutions and societal conditions in the US differ from those in other advanced economies. However, our methodology shows some differences from Mason et al. (2021) as, due to data limitations, we cannot provide a breakdown of employment by race or care responsibilities, as their study did. Additionally, while their study focuses on projections regarding potential employment, our analysis focuses on retrospective evaluations of where employment rates would be if the employment gaps were eliminated.

Second, we provide new evidence in the context of the literature on how labour market outcomes differ for men and women (e.g. Goldin 1990; Blau and Kahn 2017; Kleven et al. 2019; Cukrowska-Torzewska and Matysiak 2020) as well as for individuals with different education levels (e.g. Card 1999; Lagakos et al. 2018). While this literature has studied different labour market trajectories of men vs. women and high- vs. low-education groups in depth, we add a focus on gender and education gaps in employment across countries and regions in the EU. In particular, we provide new stylised factors on gender and education gaps at the NUTS 2 level. We show that there are significant regional differences, with the Southern and Eastern regions lagging behind in terms of both gender and education gaps. Within subregions, especially in the Eastern region, when one excludes the capital region, the employment gaps are particularly significant, indicating that the main challenge to closing the gaps lies at the subregional level. This implies that regionally targeted policies to increase employment rates are important. In the context of the European Pillar of Social Rights Action Plan, the EU already targets an overall employment rate of 78% for people aged 20 to 64 (European Commission 2022). In the future, such employment-rate targets could be set at the regional level, and policies could be aligned to meet these goals.

Third, we contribute to the literature on how cyclical conditions affect employment outcomes. There is a sizeable literature on which labour market groups suffer from cyclical swings in the economy (e.g. Hoynes et al. 2012; Akitoby et al. 2019; Huckfeldt 2022). We provide new panel econometric evidence on the cyclical behaviour of gender and education gaps in employment. Strikingly, we find that gender gaps are, on average, procyclical. More specifically, female employment rates are typically more resilient than male employment rates during downturns, and male employment rates typically grow faster than female employment rates during upswings. Our findings lend support to previous studies on how the COVID-19 crisis was atypical, as we find that gender gaps behaved differently during the pandemic than they did during previous crises (e.g. Alon et al. 2021; Albanesi and Kim 2021). From a policy perspective, our findings do not generally support hopes that sustained economic booms could reduce existing gender gaps in employment on their own. Additional targeted labour market policies may be required to improve the labour markets prospects for women. Reducing gender gaps may require the reduction of labour market obstacles, improved training programs, better workplace conditions or the expansion of childcare infrastructure. In contrast, we find that education gaps in employment are more countercyclical than gender gaps. This suggests that workers with low education benefit most from (fiscal) stabilisation measures aimed at reducing employment losses during downswings, while they may also benefit more than highly educated workers during sustained economic booms (e.g. Autor et al. 2024).

7. Conclusions

This paper has analysed employment rates by gender and education. To make aggregate groups comparable, we have adjusted employment rates by accounting for different age distributions across gender and education groups. Our findings highlight that gender and education gaps in employment differ markedly across the EU. We find larger employment gaps in Eastern and Southern Europe and smaller gaps in Nordic and Continental EU countries. In a second step of the analysis, we conduct a thought experiment and ask how much employment rates would have to rise to close existing employment gaps compared to the benchmark group of highly educated men. We find that closing education gaps between high and low education levels would raise the employment rate in the EU by 11.6 percentage points, whereas closing the gender gaps between men and women would lead to an increase of 3.8 percentage points. After providing new stylised facts, we have turned to an econometric analysis of the impact of cyclical conditions on employment gaps to better understand which groups are most affected by swings in the economy. In this case, we find that gender gaps are procyclical. On the one hand, female employment rates are typically more resilient than male employment rates during economic downturns, with the result that gender gaps tighten during crises. During upswings, on the other hand, male employment rates tend to grow at a faster pace than female employment rates, with the result that gender gaps tend to widen during booms. In contrast, education gaps are more countercyclical than gender gaps, as employment risks are significantly higher for the low-education group.

For the EU, more in-depth research would be useful on how employment gaps may evolve given the projected decline in population in many regions, especially in Eastern and Southern Europe (e.g. Stehrer and Leitner 2019). Future research could compare our results for the EU with those for other advanced economies, which would require comparable data on employment rates by gender and education. It would also be potentially fruitful to investigate the development of employment gaps in emerging market economies over time. More in-depth research could be done on policy measures used by different countries or regions to reduce gender and education gaps in employment, such as by using a case-study approach for selected advanced economies. To improve policy relevance, future research could try to identify best practice examples for how to effectively reduce existing employment gaps, where measures may differ during upswings and downswings.

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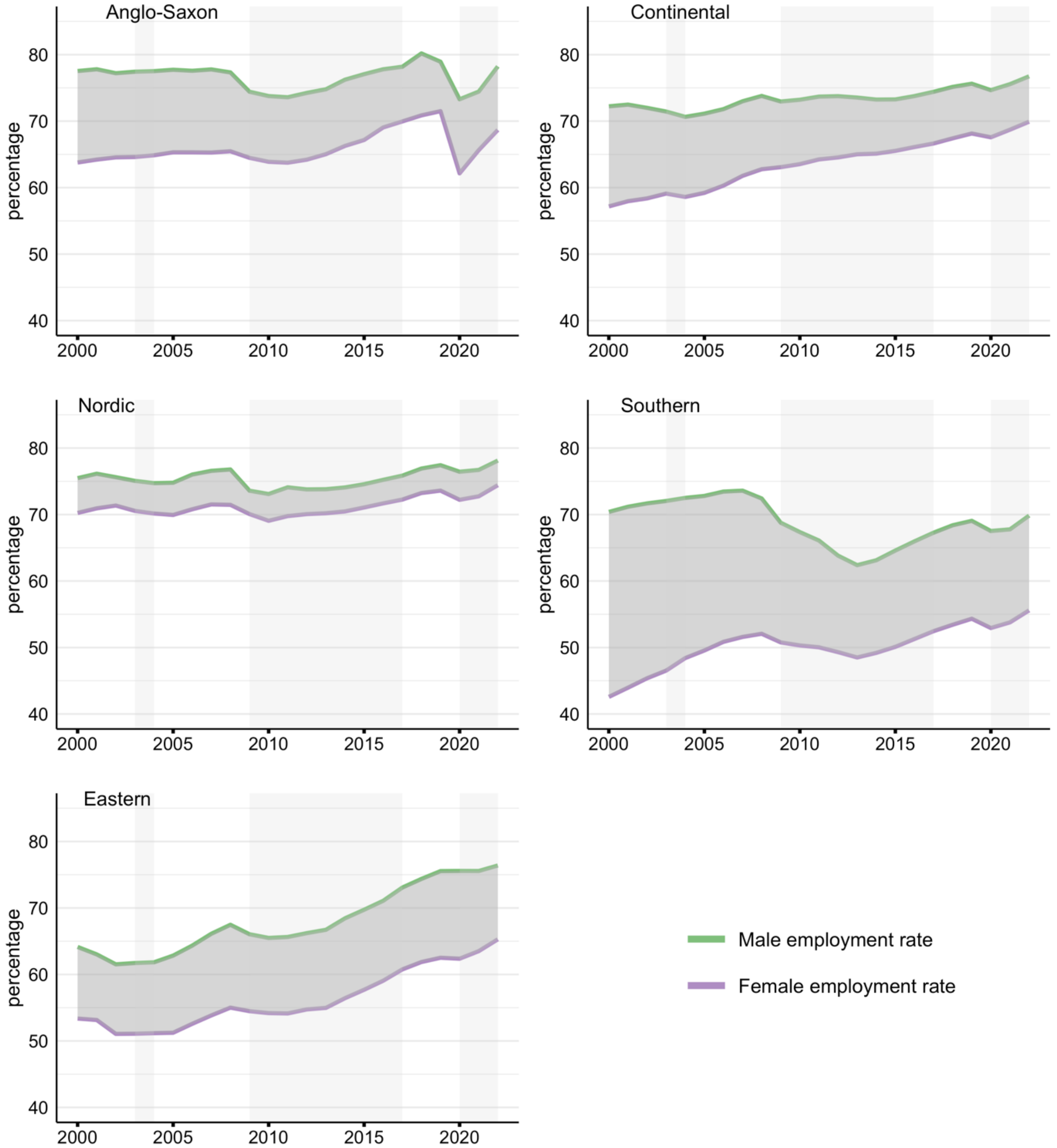
Appendix A: Additional charts

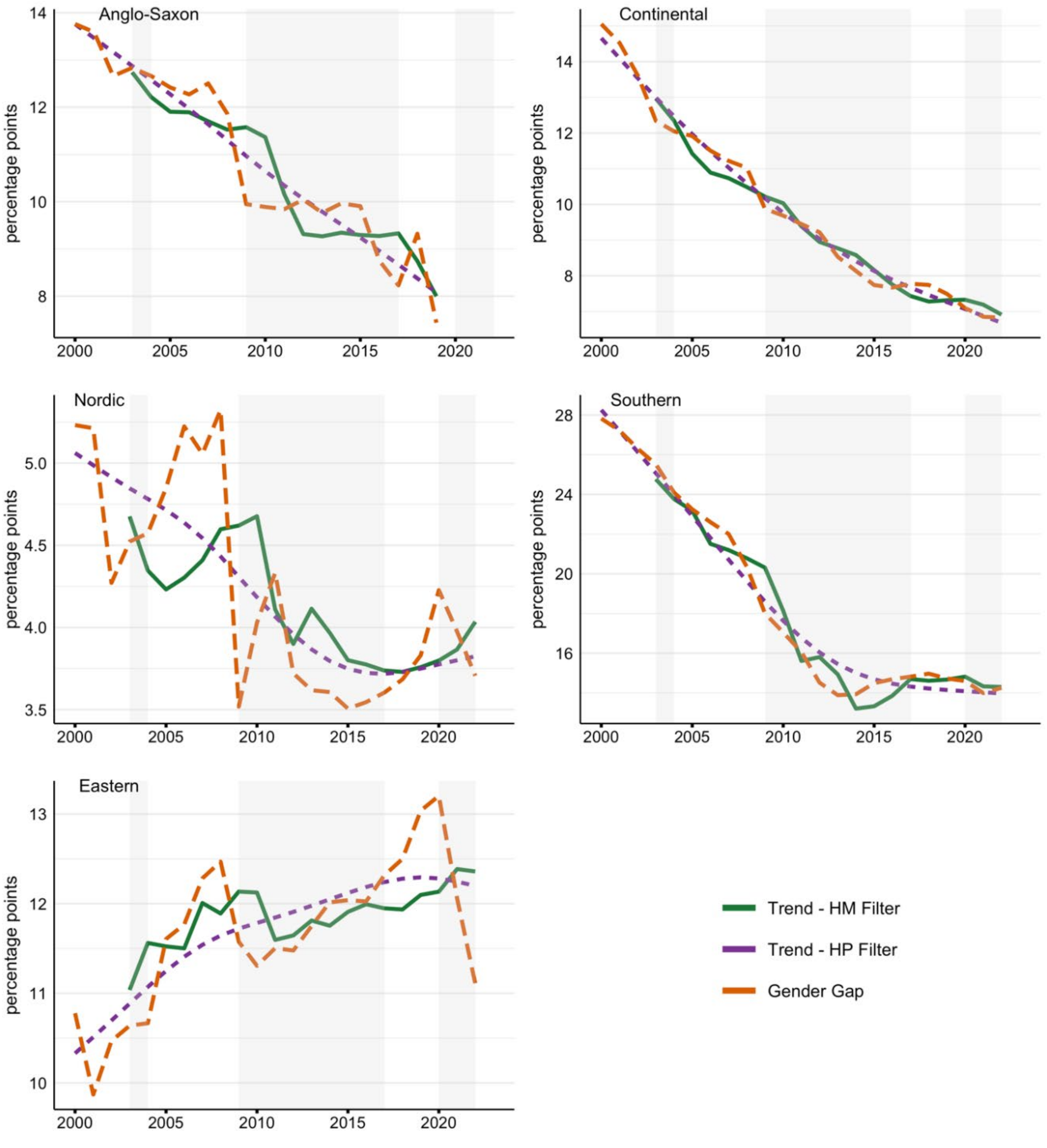
This appendix includes additional charts on the gender gap in employment and a comparison of the performance of the HP and Hamilton filters.

Figure A 1 / Female and male employment rates, 2000-2022



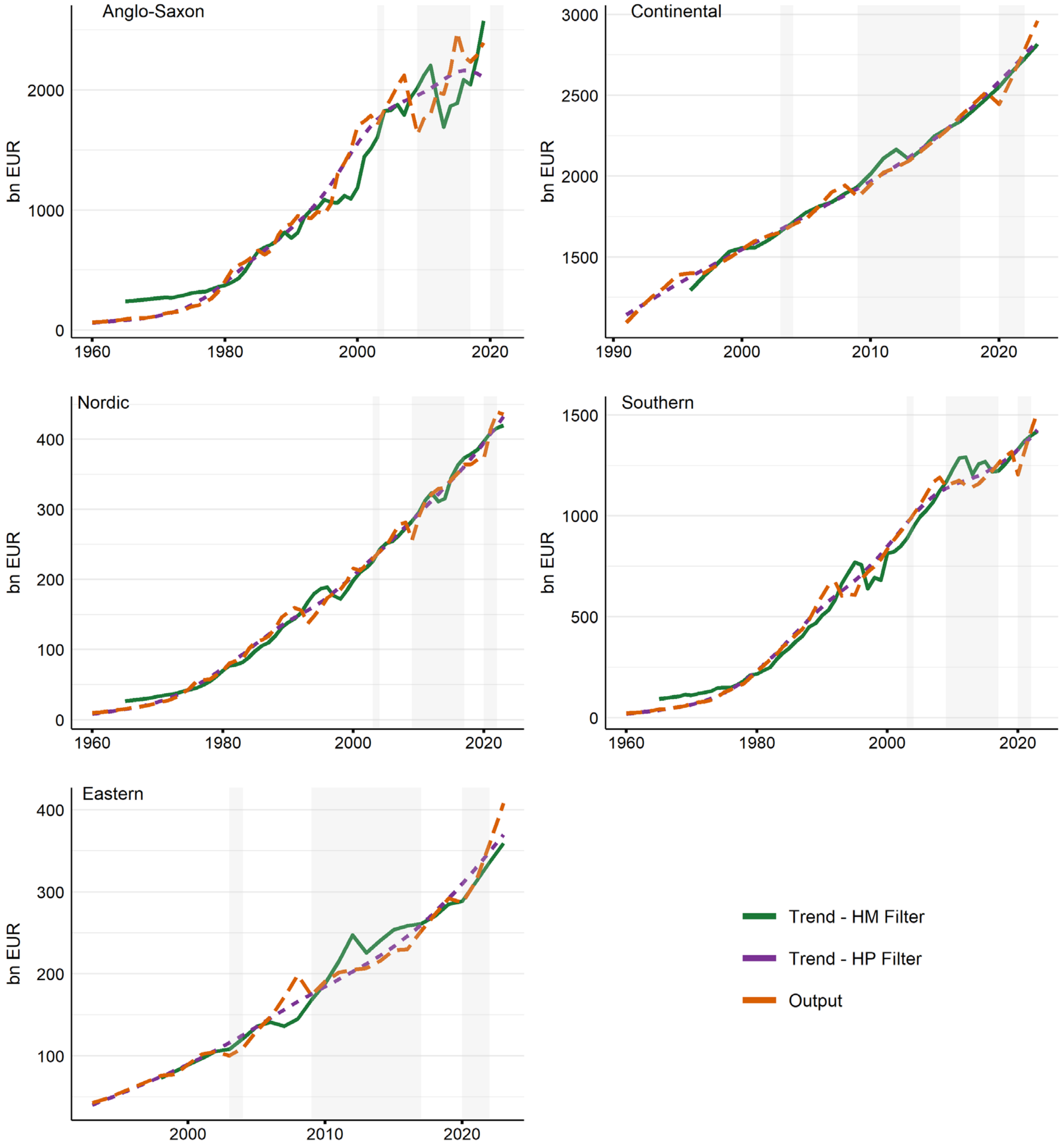
Notes: The gender gap in employment is the difference between male and female employment rates in percentage points. Employment rates are age-adjusted, with the male population serving as the reference group.
Source: Eurostat, authors' calculation.

Figure A 2 / Comparison of Hamilton and HP gender gap trends, 2000-2022



Notes: The shaded areas in the figure indicate bust periods for the EU27, which are characterised by a negative output gap. The gender gap in employment is the difference between male and female employment rates in percentage points. Employment rates are age-adjusted, with the male population serving as the reference group.
Source: Eurostat, AMECO, authors' calculation.

Figure A 3 / Comparison of Hamilton and HP output trends, 1960-2022



Notes: The shaded areas in the figure indicate bust periods for the EU27, which are characterised by a negative output gap.
Source: Eurostat, AMECO, authors' calculation.

Table A 1 / Sectoral change in employment levels in the EU27 by sector, %

Year	Gender	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
2003	Female	-0.6	NA	NA	0.8	-5.4	-1.5	1.9	1.8	1.7	-1.1	1.8	0.7	4.9	2.8	NA	3.0	5.1	2.2	1.4
2003	Male	0.6	NA	-2.2	-3.2	5.2	2.4	1.1	0.5	-0.5	-4.0	1.2	-1.8	4.9	0.8	NA	-0.4	2.9	0.0	-3.0
2004	Female	15.0	NA	NA	9.6	26.3	5.6	10.7	9.2	7.6	8.6	3.4	22.9	10.3	4.9	NA	12.7	9.0	9.5	8.4
2004	Male	13.7	NA	7.7	14.5	9.0	6.4	7.6	10.0	7.1	2.9	0.5	17.4	11.8	4.0	NA	7.2	5.6	5.3	1.7
2005	Female	-1.5	NA	NA	8.0	-4.4	1.8	1.6	0.3	5.7	-0.8	6.5	4.4	3.7	1.9	NA	0.6	2.5	3.9	7.9
2005	Male	-1.3	NA	-0.4	2.4	-1.5	3.5	1.9	0.2	3.9	2.3	2.7	7.6	3.6	0.8	NA	0.5	1.7	2.0	18.4
2006	Female	-3.2	NA	0.7	7.6	4.1	0.2	2.6	3.8	6.7	-1.9	5.0	5.2	6.1	2.9	NA	2.1	2.8	2.1	0.9
2006	Male	-2.2	NA	1.1	-0.8	5.0	4.3	1.9	3.4	3.7	1.2	0.8	5.9	4.6	-0.5	NA	-0.8	1.0	4.5	1.0
2007	**Female**	**-3.1**	NA	**1.5**	**-6.3**	**2.6**	**5.5**	**4.0**	**2.7**	**4.1**	**-1.1**	**3.3**	**2.2**	**6.7**	**2.8**	NA	**0.2**	**2.4**	**4.2**	**1.1**
2007	**Male**	**-3.9**	NA	**1.4**	**-6.8**	**0.4**	**5.8**	**2.6**	**3.1**	**1.9**	**1.0**	**0.8**	**2.8**	**4.9**	**0.2**	NA	**-0.3**	**1.3**	**3.4**	**-6.4**
2008	**Female**	**-4.1**	NA	**-5.3**	**-1.2**	**221.5**	**12.1**	**0.7**	**27.2**	**1.0**	**46.6**	**0.7**	**-13**	**-42**	**-42**	NA	**2.4**	**1.8**	**-46**	**34.7**
2008	**Male**	**-6.3**	NA	**-2.9**	**4.6**	**255.5**	**1.6**	**-1.4**	**12.1**	**1.6**	**100.0**	**1.6**	**-13**	**-47**	**-54**	NA	**3.5**	**-1.3**	**-42**	**13.2**
2009	**Female**	**-1.6**	**-10**	**-8.0**	**7.5**	**-1.9**	**-5.0**	**-1.5**	**-2.1**	**-0.2**	**-1.4**	**0.6**	**0.7**	**1.7**	**-0.2**	**2.0**	**0.7**	**2.6**	**-0.5**	**-0.9**
2009	**Male**	**-1.0**	**-5.1**	**-6.2**	**5.5**	**0.6**	**-6.4**	**-2.1**	**-2.5**	**0.1**	**2.1**	**1.1**	**-3.3**	**-1.8**	**1.4**	**-0.4**	**-0.6**	**2.6**	**-0.6**	**-8.2**
2010	**Female**	**-3.5**	**-1.4**	**-5.8**	**-1.7**	**2.2**	**-4.4**	**-2.4**	**-2.4**	**-1.0**	**-1.1**	**-2.6**	**-0.7**	**-1.2**	**-0.4**	**-0.9**	**0.8**	**1.6**	**-0.6**	**0.4**
2010	**Male**	**0.6**	**-1.4**	**-4.2**	**-0.2**	**-1.3**	**-5.1**	**-1.9**	**-1.8**	**0.4**	**0.9**	**0.0**	**-0.4**	**0.5**	**2.3**	**-0.2**	**-1.8**	**2.9**	**1.2**	**-2.9**
2011	Female	-4.3	0.1	0.4	2.5	4.3	-0.3	-0.3	-2.0	1.2	0.3	1.8	2.5	2.7	2.0	-1.4	0.1	1.5	0.9	-1.9
2011	Male	-3.5	-0.6	0.4	-1.4	2.3	-4.1	-0.9	0.7	0.5	0.5	-0.8	2.0	2.4	2.5	-0.5	0.4	1.8	0.1	0.1
2012	Female	-2.7	-7.7	-1.4	6.4	3.7	-2.5	-0.7	-0.1	-0.7	2.2	-0.3	-2.1	0.3	2.3	-1.2	1.2	1.3	2.6	-0.2
2012	Male	0.5	-1.2	-1.7	-0.3	1.5	-3.9	-0.3	-0.8	1.6	1.9	-1.3	0.9	-0.4	1.9	-2.6	0.6	2.0	-0.2	0.6
2013	Female	-4.9	-1.6	-1.9	-1.3	-3.7	0.4	0.5	0.9	-0.7	-5.8	0.0	1.2	2.2	0.4	-0.6	0.2	0.9	0.8	2.4
2013	Male	-1.2	-0.2	-1.2	-2.9	0.9	-4.3	2.3	0.8	-1.1	-2.0	0.1	1.9	4.8	-1.1	-1.7	-0.4	-2	2.6	0.9
2014	Female	-2.6	-3.4	1.5	-3.5	1.6	-1.2	0.9	2.1	1.9	2.0	-1.2	-0.9	3.2	2.8	1.0	2.6	2.5	3.6	-2.2
2014	Male	-1.0	-0.8	1.5	-2.4	0.1	-1.1	-0.2	0.4	3.5	1.6	-0.3	5.6	2.9	3.7	1.1	2.3	2.6	3.6	-1.8
2015	Female	-4.7	-4.7	0.3	-1.9	3.2	-2.8	1.3	0.7	3.1	1.2	0.6	5.5	2.9	1.4	1.2	1.8	1.5	4.8	0.4
2015	Male	-1.1	-6.8	1.2	-2.5	2.4	0.4	0.5	1.7	5.8	4.0	-1.3	-2.0	1.4	3.6	0.1	0.0	0.1	2.9	-0.9
2016	Female	-6.7	11.8	1.6	-4.4	-1.3	1.1	1.3	2.5	4.5	2.0	0.3	-1.0	4.0	1.0	2.2	1.3	1.5	2.1	1.9
2016	Male	-2.1	-3.2	2.1	1.5	-0.5	0.6	1.4	2.9	3.0	2.9	2.2	-3.4	2.1	2.7	-0.7	0.0	3.8	2.7	2.1
2017	Female	-1.2	-0.1	2.7	4.2	4.6	5.5	-0.5	1.8	2.0	2.7	0.2	-1.9	2.5	1.8	1.0	1.2	1.9	1.1	2.8
2017	Male	-1.8	-6.1	1.4	-2.2	4.1	2.0	1.6	2.6	1.9	3.5	-0.2	8.6	2.0	0.6	-0.5	1.1	1.2	1.2	1.8
2018	Female	-3.5	-7.0	1.1	4.1	4.8	2.2	0.3	0.6	1.4	2.9	-0.4	3.7	1.4	2.8	0.9	2.3	1.3	0.7	0.2
2018	Male	-2.9	-3.5	0.6	-1.0	2.5	1.5	0.2	1.3	2.5	5.2	-0.8	-3.1	2.2	0.3	0.4	0.8	1.2	1.1	4.0
2019	Female	-2.4	2.8	0.0	5.0	9.5	2.3	-0.3	2.8	0.7	4.6	-0.4	3.7	4.0	0.6	0.6	1.5	1.9	2.3	1.3
2019	Male	-1.7	0.8	0.2	2.7	0.7	1.3	0.3	1.2	0.6	4.0	-0.5	-2.6	1.7	2.1	-1.0	2.5	2.2	4.2	-1.4
2020	**Female**	**-3.5**	**7.3**	**-2.2**	**6.4**	**-4.0**	**-2.9**	**-1.8**	**-5.0**	**-14**	**6.9**	**2.2**	**7.3**	**0.2**	**-8.3**	**6.0**	**-1.3**	**-1**	**-5.2**	**2.0**
2020	**Male**	**-1.4**	**1.0**	**-0.7**	**2.4**	**0.7**	**-4.1**	**-4.9**	**-3.7**	**-11**	**7.9**	**3.3**	**7.9**	**-1.9**	**-8.2**	**2.5**	**1.6**	**0.0**	**-5.4**	**17.2**
2021	**Female**	**-14**	**-3.8**	**0.5**	**9.5**	**3.6**	**7.7**	**0.5**	**3.1**	**-3.7**	**8.0**	**1.9**	**2.0**	**3.0**	**1.4**	**0.9**	**3.6**	**2.8**	**0.6**	**3.6**
2021	**Male**	**-7.3**	**-7.1**	**-1.5**	**0.3**	**0.0**	**1.3**	**1.9**	**2.0**	**-4.4**	**6.0**	**1.5**	**3.6**	**3.7**	**3.2**	**-1.1**	**0.8**	**2.6**	**-3.2**	**2.8**
2022	Female	-0.3	-2.2	2.2	-4.0	5.1	4.6	1.9	2.7	13.6	4.2	-0.4	4.4	4.5	6.6	0.6	1.5	2.1	8.9	1.4
2022	Male	-1.6	-2.3	-0.1	-0.4	0.1	3.4	1.6	2.1	15.1	4.8	0.4	5.5	4.1	5.6	-0.3	0.4	1.1	12.9	-0.2

Source: Eurostat, AMECO, authors' calculation.

Appendix B: Sensitivity checks and robustness tests

An overview of the variables used and descriptive statistics are shown in Table A 2 and Table A 3, respectively.

Table A 2 / Variables used in the multivariate regression analysis in Section 5

Variable	Unit	Source
Gender gap	Percentage points of total population	Eurostat; own calculations
Education gap (high-low)	Percentage points of total population	Eurostat; own calculations
Output gap	Gap between actual and potential output (in % of potential output)	AMECO
Real GDP growth	Annual growth rate (%)	AMECO; own calculations
Unemployment rate	Percent of active population	AMECO
Employment protection legislation	Index for strictness of employment protection (individual and collective dismissals, regular contracts)	OECD
Trade union density	Share of employees who are union members (%)	OECD
Economic globalisation	Economic globalisation index (0-100)	KOF (Gygli et al., 2019)
TFP growth	Total factor productivity (annual growth rate, %)	AMECO; own calculations
Age-dependency ratio	Ratio of population 0-14 years and 65 years or over to population 15-64 years	OECD; own calculations
Fertility rate	Mean number of children per woman	
Real wage growth	Annual growth rate (%)	AMECO; own calculations.
Left-right dimension of government	Degree of the current government, from very right (0) to very left (10)	ERDDA, ParlGov, CPDS and V-Party; own calculations

Note: Own illustration.

Table A 3 / Descriptive statistics of used variables

Statistic	N	Mean	St. Dev.	Min.	Max.
Year	470	2,011.54	5.49	2,000.00	2,020.00
Employment rate	357	71.41	5.58	53.99	82.10
Max. employment rate / education gap closed	357	83.12	3.94	67.20	90.16
Max. employment rate / gender gap closed	357	74.96	5.42	61.03	85.41
Max. employment rate / education and gender gaps closed	357	86.80	3.60	71.92	93.49
Output gap	470	-0.70	3.88	-19.40	11.43
Growth	470	1.78	3.89	-14.84	24.48
Unemployment rate	470	8.63	4.31	2.02	27.80
Employment protection law	353	2.34	0.85	0.09	4.58
Union density	333	27.34	18.85	4.50	81.00
Total factor productivity	470	0.34	2.88	-12.08	21.43
Economic globalisation	454	78.51	6.58	61.37	93.03
Age dependency ratio	448	49.89	4.59	38.60	62.10
Fertility rate	447	1.54	0.20	1.13	2.06
Real wage growth	434	3.34	4.17	-10.91	34.80
Left- / Right-wing governments	385	5.31	1.54	2.66	8.80

We perform a Spearman correlation analysis and compute the variance inflation factor (VIF) to check for potential multicollinearity of key variables in our baseline estimation set-up. Spearman correlations among explanatory variables for our regressions are reported in Table A 4 and do not point to any evidence of considerable correlations (beyond 0.9 or -0.9). The highest detected correlation exists between EMPL ¬and UNR and is at -0.66, which is of no concern.

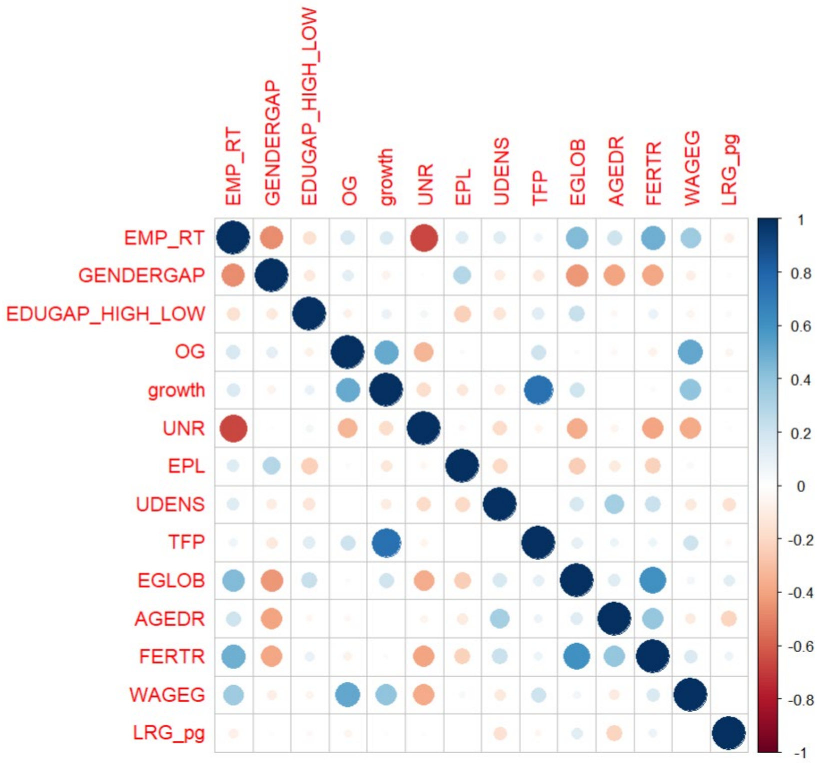
The VIF outcomes on the econometric regression approaches presented in Section 5 are very similar for the specifications in which the gender gap and the high-low education gap are used as dependent variables (see Table A 5). When the output gap or unemployment rate are used to account for cyclicality, the VIF lies between one and two, which shows that no multicollinearity is present in these cases. However, for regression specifications that use GDP growth, we find VIF values above five for GDP growth and TFP. Such values do indicate a considerable degree of multicollinearity, which inflates the explanation of the data variance by a factor of more than five compared to a model without multicollinearity. However, as the specification with GDP growth is not our only regression set-up and because results of the more robust specifications with output gap and unemployment also mimic the regression outcome (as in the case of GDP growth), this does not cast doubt on the general conclusions gained from the econometric analysis (see Table 4 and Table 5 in Section 5).

Table A 4 / Spearman correlation analysis in tabular form with values (upper table) and a graphical representation in the form of a correlation plot (lower table)

	EMP_RT	GENDERGAP	EDUGAP_HIGH_LOW	OG	Growth	UNR	EPL	UDENS	TFP	EGLOB	AGEDR	FERTR	WAGEG	LRG_pg
EMP_RT	1	-0.47	-0.16	0.17	0.15	-0.66	0.13	0.13	0.07	0.44	0.21	0.48	0.35	-0.08
GENDERGAP	-0.47	1	-0.12	0.12	-0.06	0.01	0.28	-0.09	-0.12	-0.43	-0.40	-0.39	-0.09	0.02
EDUGAP_HIGH_LOW	-0.16	-0.12	1	-0.07	0.09	0.05	-0.24	-0.13	0.12	0.23	-0.05	0.09	-0.06	-0.03
OG	0.17	0.12	-0.07	1	0.51	-0.33	0.03	0	0.20	0.03	-0.04	-0.07	0.52	-0.06
Growth	0.15	-0.06	0.09	0.51	1	-0.17	-0.12	-0.10	0.75	0.19	0	0.02	0.39	0.02
UNR	-0.66	0.01	0.05	-0.33	-0.17	1	-0.05	-0.18	-0.05	-0.37	-0.06	-0.40	-0.38	0.02
EPL	0.13	0.28	-0.24	0.03	-0.12	-0.05	1	-0.20	0	-0.24	-0.11	-0.23	0.04	0.01
UDENS	0.13	-0.09	-0.13	0	-0.10	-0.18	-0.20	1	0	0.16	0.34	0.22	-0.11	-0.16
TFP	0.07	-0.12	0.12	0.20	0.75	-0.05	0	0	1	0.11	0.07	0.07	0.20	-0.04
EGLOB	0.44	-0.43	0.23	0.03	0.19	-0.37	-0.24	0.16	0.11	1	0.13	0.61	0.05	0.12
AGEDR	0.21	-0.40	-0.05	-0.04	0	-0.06	-0.11	0.34	0.07	0.13	1	0.38	-0.10	-0.21
FERTR	0.48	-0.39	0.09	-0.07	0.02	-0.40	-0.23	0.22	0.07	0.61	0.38	1	0.15	0.07
WAGEG	0.35	-0.09	-0.06	0.52	0.39	-0.38	0.04	-0.11	0.20	0.05	-0.10	0.15	1	-0.01
LRG_pg	-0.08	0.02	-0.03	-0.06	0.02	0.02	0.01	-0.16	-0.04	0.12	-0.21	0.07	-0.01	1

Source: Own calculations.

Figure A 4 / Bivariate correlations



Source: Own calculations.

Table A 5 / VIF test outcomes

Dep. Variable	OG	Growth	UNR	EPL	UDENS	TFP	EGLOB	AGEDR	FERTR	WAGEG	LRG
GENDERGAP	1.79			1.17	1.32	1.14	1.55	1.56	1.93	1.72	1.13
		6.64		1.23	1.31	5.81	1.63	1.57	2.04	1.33	1.15
			1.64	1.24	1.31	1.10	1.64	1.56	1.98	1.42	1.15
EDUGAP_HI_LOW	1.79			1.17	1.31	1.14	1.55	1.56	1.93	1.72	1.13
		6.64		1.23	1.31	5.81	1.63	1.57	2.04	1.33	1.15
			1.64	1.24	1.31	1.10	1.64	1.56	1.98	1.42	1.15

Source: Own calculations.

Results of the Maddala-Wu panel unit root test that we applied to our panel dataset variables are depicted in Table A 6. The Maddala-Wu (MW) test is a Fisher-type test that combines p-values from tests based on Augmented Dickey-Fuller (ADF) regressions per individual available. In contrast to the Im-Pesaran-Shin (IPS) test, which assumes asymptotic validity regarding the amount of N individuals going to infinity, the Fisher test depends on T going to infinity (Maddala and Wu 1999). As Table A 6 shows, the MW test reports panel stationarity for the regression set-ups with GENDERGAP as our dependent variable (Test 1x) as well as for EDUGAP_HIGH_LOW as our dependent variable (Test 2x).

If time series variables do not exhibit stationarity, they can still show a stable long-term relationship together (i.e. they can be cointegrated with each other), which can impact the model estimation. As the MW test indicates a stationary panel, it would not be required to conduct cointegration tests. However, for the sake of completeness, we integrate a battery of cointegration tests to test for cointegrating relationships in our panel. We will base our conclusions on the Pedroni test results, as it is the most comprehensive cointegration test due to its ability to detect both homogenous and heterogenous cointegration relationships. Test results of the Kao and Fisher test are also added in order to provide more information on our data structures. As Table A 7 shows, we do not find any sign of clear cointegration in our panel data. Thus, there is also no need or possibility to specify a correct vector error correction model, and the specification of our econometric model in Section 5 is therefore validated.

Table A 6 / Panel unit root test results based on the Maddala-Wu test

	Test 1a	Test 1b	Test 1c	Test 2a	Test 2b	Test 2c
Independent variable	GENDER GAP	GENDER GAP	GENDER GAP	EDUGAP_ HIGH_LOW	EDUGAP_ HIGH_LOW	EDUGAP_ HIGH_LOW
Cyclical control variable	OG_{t-1}	$GDPgrowth_{t-1}$	UNR_{t-1}	OG_{t-1}	$GDPgrowth_{t-1}$	UNR_{t-1}
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Unit root test result	**$p < 0.01$**	**$p < 0.01$**	**$p < 0.01$**	**$p < 0.01$**	**$p < 0.01$**	**$p < 0.01$**

Source: Own calculations.

Table A 7 / Cointegration tests for variables used in the baseline econometric specification

	Variables	Pedroni test[7] [H0: no cointegration]	Kao test[8] [H0: no cointegration]	Fisher test[9] [H0: no cointegration]
(1a)	OG_{t-1}, EPL_{t-1}, $UDENS_{t-1}$, TFP_{t-1}, $EGLOB_{t-1}$, $AGEDR_{t-1}$, $FERTR_{t-1}$	$p > 0.10$ for 6 / 11 test statistics	$p < 0.01$	$p < 0.01$ (max. of 2 cointegrating relationships)
(1b)	OG_{t-1}, TFP_{t-1}, $EGLOB_{t-1}$, $AGEDR_{t-1}$, $FERTR_{t-1}$, $WAGEG_{t-1}$, LRG_pg_{t-1},	$p > 0.10$ for 9 / 11 test statistics	$p < 0.01$	$p < 0.01$ (max. of 1 cointegrating relationship)
(2a)	$growth_{t-1}$, EPL_{t-1}, $UDENS_{t-1}$, TFP_{t-1}, $EGLOB_{t-1}$, $AGEDR_{t-1}$, $FERTR_{t-1}$	$p > 0.10$ for 8 / 11 test statistics	$p < 0.01$	$p < 0.01$ (max. of 3 cointegrating relationships)
(2b)	$growth_{t-1}$, TFP_{t-1}, $EGLOB_{t-1}$, $AGEDR_{t-1}$, $FERTR_{t-1}$, $WAGEG_{t-1}$, LRG_pg_{t-1},	$p > 0.10$ for 7 / 11 test statistics	$p < 0.01$	$p < 0.01$ (max. of 2 cointegrating relationship)
(3a)	UNR_{t-1}, EPL_{t-1}, $UDENS_{t-1}$, TFP_{t-1}, $EGLOB_{t-1}$, $AGEDR_{t-1}$, $FERTR_{t-1}$	$p > 0.10$ for 8 / 11 test statistics	$p < 0.01$	$p < 0.01$ (max. of 3 cointegrating relationships)
(3b)	UNR_{t-1}, TFP_{t-1}, $EGLOB_{t-1}$, $AGEDR_{t-1}$, $FERTR_{t-1}$, $WAGEG_{t-1}$, LRG_pg_{t-1},	$p > 0.10$ for 7 / 11 test statistics	$p < 0.05$	$p < 0.01$ (max. of 2 cointegrating relationship)
(4)	All baseline variables	–	$p < 0.01$	–

7 Pedroni residual cointegration test based on Pedroni (1999), conducted in EViews10+ with the assumptions of a deterministic intercept and trend and an automatically selected lag length based on Schwarz information criterion.

8 Kao test based on Engle-Granger, conducted in EViews10+ with the assumption of an individual intercept and an automatically selected lag length based on the Schwarz information criterion.

9 Johansen-Fisher panel cointegration test, conducted in EViews10+ with the assumption of a linear trend in the level data as well as an intercept and a trend in the cointegration equations; the lag specification for differenced endogenous is assumed to be 1.

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Offenlegung nach § 25 Mediengesetz: Medieninhaber (Verleger): Verein "Wiener Institut für Internationale Wirtschaftsvergleiche", A 1060 Wien, Rahlgasse 3. Vereinszweck: Analyse der wirtschaftlichen Entwicklung der zentral- und osteuropäischen Länder sowie anderer Transformationswirtschaften sowohl mittels empirischer als auch theoretischer Studien und ihre Veröffentlichung; Erbringung von Beratungsleistungen für Regierungs- und Verwaltungsstellen, Firmen und Institutionen.

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